Automated Visual Defect Detection for Flat Steel Surface: A Survey

Qiwu Luo, *Member, IEEE*, Xiaoxin Fang, Li Liu, Chunhua Yang, *Member, IEEE*, and Yichuang Sun, *Senior Member, IEEE*

***Abstract*—Automated computer-vision-based defect detection has received much attention with the increasing surface quality assurance demands for the industrial manufacturing of flat steels. This article attempts to present a comprehensive survey on surface defect detection technologies by reviewing about 120 publications over the last two decades for three typical flat steel products of con-casting slabs and hot- and cold-rolled steel strips. According to the nature of algorithms as well as image features, the existing methodologies are categorized into four groups: statistical, spectral, model-based, and machine learning. These works are summarized in this review to enable easy referral to suitable methods for diverse application scenarios in steel mills. Realization recommendations and future research trends are also addressed at an abstract level.**

***Index Terms*—Automated optical inspection (AOI), automated visual inspection (AVI), flat steel, surface defect detection, survey.**

I. Introduction

As a dominant steel product, flat steel occupies more than 65% of all the products in the iron and steel industry, which is the vital fundamental material for the related planar industries, including without limitation, architecture, aerospace, machinery, automobile, and so on. Any quality problems suffering on flat steel would lead to huge economic and reputation losses to steel manufacturers. For thin and wide flat steel, surface defects are the greatest threat to the product quality. Even for occasional internal defects, morphological changes will arise on the surface with large probability. Automated visual inspection (AVI) instrument targeting on surface quality emerges as a standard configuration for flat steel mills to improve product quality and promote production efficiency.

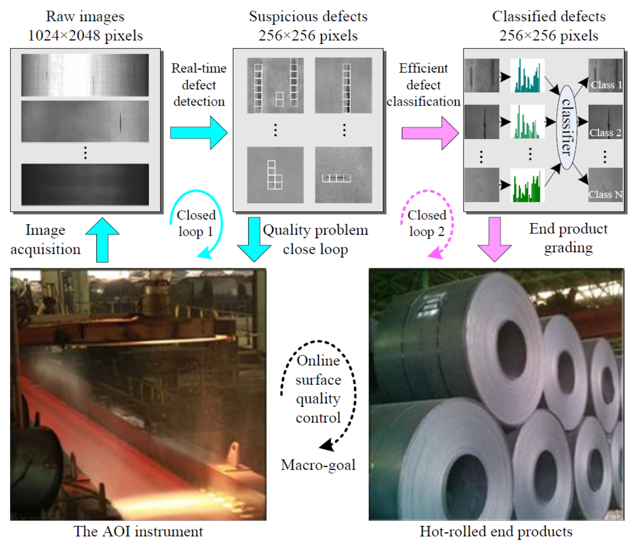


Fig. 1. Contribution of defect detection in a typical AVI instrument.

A general AVI instrument provides two main functions of defect detection and classification [1]–[4]. The former detection process recognizes the defective regions from normal background without identifying what types of defects they are. This step is the foundation of the "quality problem closed loop," and earlier defect detection allows less economic losses. The latter process is dedicated to identify and label detected defects to support finishing product grading. In this context, the flat steel covers three categories of con-casting slabs and hot- and cold-rolled steel strips, where slabs are rolled into hot strips and then to cold strips. Taking a hot strip as an example, Fig. 1 briefly shows the flowchart of AVI processes. In general, defect detection is required to be in strict real-time, while defect classification can be handled in quasi-real-time. The total performance of the AVI system is mainly limited by the accuracy, time efficiency, and robustness of the arithmetical methods in the defect detection process, which is the very focus of this article.

However, on-site surface defect detection in real-world steel mills is seriously challenging, which is given in the following.

1) *Unsatisfactory Imaging Environments:* Continuous casting and rolling production lines involve multiple

Manuscript received August 27, 2019; revised November 12, 2019; accepted December 17, 2019. Date of publication January 1, 2020; date of current version February 10, 2020. This work was supported in part by the National Natural Science Foundation of China under Grant 51704089 and Grant 61973323 and in part by the Anhui Provincial Natural Science Foundation of China under Grant 1808085QF190. The Associate Editor coordinating the review process was Shutao Li. *(Corresponding author: Chunhua Yang.)*

Qiwu Luo and Chunhua Yang are with the School of Automation, Central South University, Changsha 410083, China (e-mail: ychh@csu.edu.cn).

Xiaoxin Fang is with the School of Electrical and Automation Engineering, Hefei University of Technology, Hefei 230009, China.

Li Liu is with the Center for Machine Vision and Signal Analysis, University of Oulu, 90014 Oulu, Finland, and also with the College of System Engineering, National University of Defense Technology, Changsha 410073, China.

Yichuang Sun is with the School of Engineering and Computer Science, University of Hertfordshire, Hatfield ALl0 9AB, U.K.

Color versions of one or more of the figures in this article are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TIM.2019.2963555

sufferings of high temperature, dense mist, heavy cooling water drops [5], uneven illumination, stochastic noises [1], [2], and aperiodic vibration [6]. The undesirable image quality requires preeminent detection algorithms to resist large intraclass variation and minor interclass distance [1]–[4].

2) *Eternally Continuous Image Streams:* The online dual-surface quality measurement for average flat steel mills requires the surface AVI instrument to continuously process about 2.56 Gb/s of image flows [5] to identify defective regions, which force the detection algorithms to achieve excellent balance between accuracy, computational complexity, and reliability.

Over the years, industry and academia devote themselves to address the aforementioned challenges from hardware upgrade to algorithmic optimization. The hardware architecture based on either server expansion [7]–[9] or application-specific integrated circuit (ASIC) acceleration [5] has been opened in some recent reports. Furthermore, it is not easy to see dramatic hardware breakthroughs within a relatively short time due to the limitation of Moore's law [10]. This review thus focuses on the latest theoretical and algorithmic advances of automated visual defect detection over the past two decades to enable easy referral to suitable methods for diverse application scenarios in steel mills. Especially, the works over the last five years accounted for nearly 50%.

The structure of this context is as follows. After the introduction in Section I, some relevant prior survey articles are briefly reviewed in Section II. Typical defect morphologies on flat steel surfaces are illustrated vividly in Section III. The four categories of defect detection approaches are presented in Section IV in detail. This article is ended in Section V with the conclusion and comments on the realization recommendations and future research trends.

II. Prior Literature Review

A number of AVI surveys (such as [11]–[13]) with a wide coverage of inspection problems can be available successively. Recently published surveys gradually pay more attention to specific planar materials, such as fabric [8] and semiconductor [14]. Notably, a brief but rare AVI review covering defect detection and classification techniques for steel products was reported [9], where nearly all types of steel products (slab, billet, plate, hot strip, cold strip, and rod/bar) are involved at an overview level. It is widely recognized that AVI techniques are more suitable to inspect surface defects on sheet materials than on wire rod/bar with minor diameter or even special-shaped structures [15]. To further narrow the scope of [9], that is, concentrate on the vital defect detection process on only flat steel products, this article attempts to present a first transactions survey on this focused topic so as to support the AVI applications for the relevant industrial manufacturing.

III. Defect Morphologies on Flat Steel Surface

Various defects on flat steel surface are generally caused by mechanical or metallurgical imperfection during the industrial manufacturing. To save article space, we only take some surface defect image samples for hot-rolled steel strips and con-casting slabs by using the AVI instrument designed in [5] for illustration. Fig. 2(a) shows four raw defective images (4096×1024 pixels) acquired by the equipped line-scan camera, and Fig. 2(b) shows 18 typical defect samples with 256×256 pixels obtained from raw images after the defect detection process. These are roller marks, longitudinal scratches, horizontal scratches, inclusions, scarring, holes, waves, pitting, air bubbles, peeling, water droplets, convex bags, reticulations, star cracks, foreign bodies, heavy leather, wrinkles, and longitudinal cracks, respectively. Finally, in Fig. 2(c), some longitudinal crack image samples of con-casting slabs are presented (512×512 pixels), and this defect type is with high probability of occurrence on continuous casting line, which has great threat to the quality of downstream products. Besides the diversity and complexity of these defects, nearly, all the challenges mentioned in Section I can be encountered in these image samples. For example, some pseudodefects of water droplets and mill scales are pretty commonly distributing on the surfaces of hot-rolled strips and casting slabs, which would trigger false detection. In another example, the image intensity is fairly inhomogeneous and varies actively.

IV. Taxonomy of Defect Detection Methods

This section presents a review on the prior techniques and models for defect detection of flat steel surfaces. In general, researchers categorize previously proposed methods into different groups based on the distinct features, while the taxonomy also varies from person to person. Fofi *et al.* [16] broadly separated the texture defect detection approaches into local and global groups. According to different technique roadmaps, defect detection methods are summarized as classification-, local-abnormality-, and template-matching-based methods in [17]. Youkachen *et al.* [18] classified the defect detection methods into probabilistic-, statistical-, proximity-, deviation-, and network-based models. At the microscopic level, the flat steel surface inspection problem is essentially a texture analysis problem [8]. Normally, texture analysis problem can be solved by statistical-, spectral-, and model-based methods. Notably, machine learning enjoys its popularity in computer vision in recent years, especially in texture analysis. Thus, as shown in Fig. 3, this article classifies defect detection methods for flat steel surfaces into four categories: conventional statistical, spectral, model-based, and emerging machine learning.

A. Statistical

Statistical approaches are frequently used to detect the defects of flat steel surface by evaluating the regular and periodic distribution of pixel intensities. Eight representative statistical methods are briefly introduced as follows.

1) Thresholding: Thresholding methods are usually used to separate the defective regions on flat steel surfaces, which have been widely applied in online AVI systems [19], [20]. The traditional thresholding methods identify the defects by comparing the value of image pixels to a fix number and

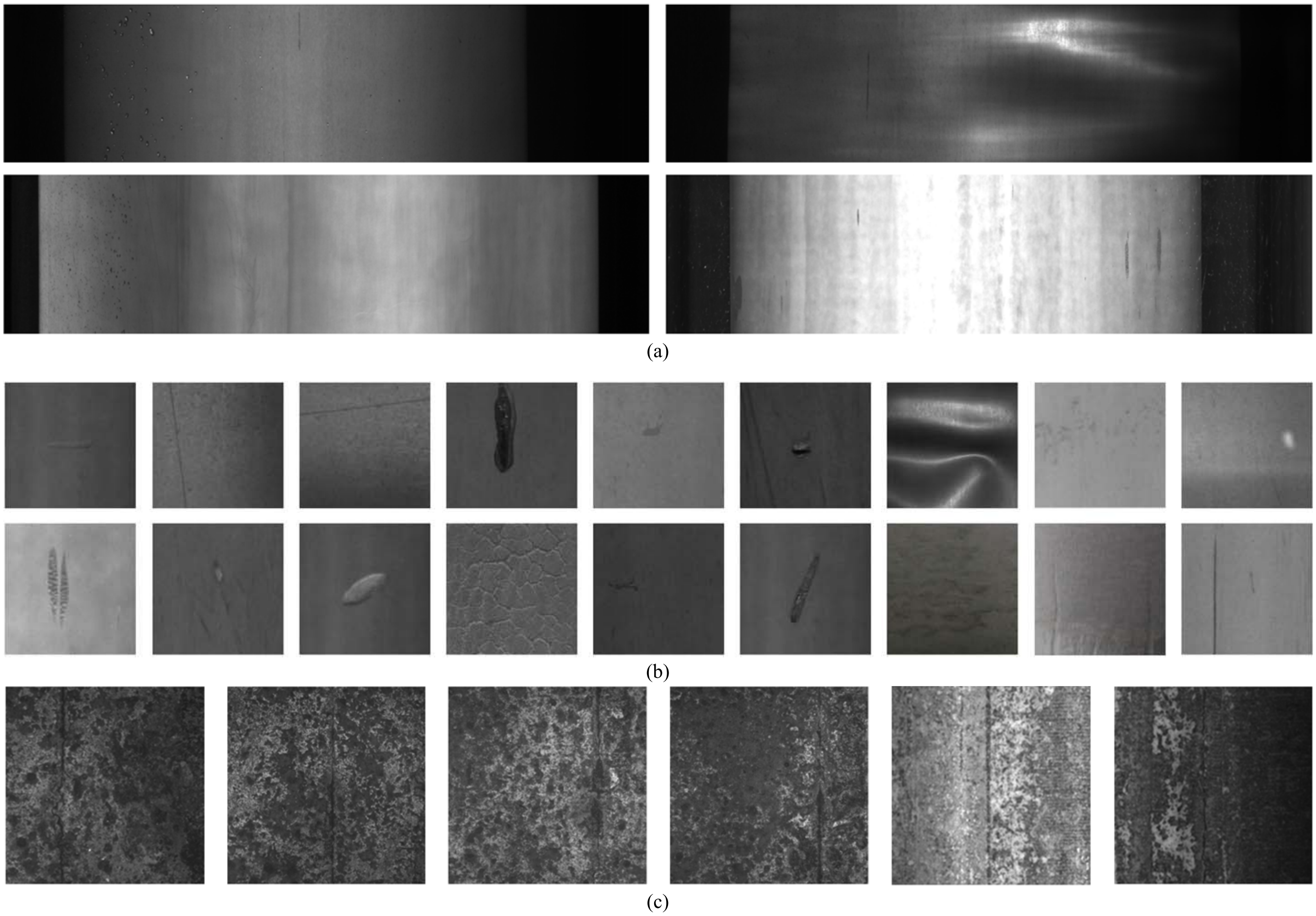


Fig. 2. Typical defect image samples. (a) Typical defective raw images of steel surface (4096 × 1024 pixels) acquired by line-scan camera and (b) series of typical defect samples with 256 × 256 pixels for hot-rolled steel strips. (c) Typical longitudinal cracks acquired by area-scan camera for con-casting slabs.

turn the test image into a simple binary frame, which is sensitive to random noises and nonuniform illuminations. Djukic and Spuzic [21] first estimated the probability distribution of pixel intensities from some defect-free hot-rolled steel images, which was considered as a basis for adaptively determining threshold. The dynamical thresholding procedure can then discriminately separate true defects from random noise. Furthermore, Nand *et al.* [22] calculated the local entropy of defective and defect-free images and extracted the defective region of image by using background subtraction method by comparing their entropy, and it is reported to perform better on detecting defective blocks of low-quality steel surface than the former dynamical thresholding method. To obtain a better global detection performance, Neogi *et al.* [23] proposed a global adaptive percentile thresholding scheme based on gradient images. It can selectively segment the defective region and effectively preserve the defect edges regardless of the size of defects. In order to further accomplish the task of defect detection, it is promising to obtain the optimal thresholds or design a smarter dynamic thresholding mechanism.

2) Clustering: Based on the similarity among image pixels, the clustering method is specialized in mining information implicitly existing in texture images, and then, defect detection can be achieved by the multiple-class defect classification. Real-time and antinoise capability are always the basic requirements of industrial defect detection; Bulnes *et al.* [24] detected the defects occurring periodically by clustering the characteristics (i.e., position and type) of each defect. This method can timely detect the periodical defects even in a noisy environment. However, some interferences, such as stochastic industrial liquids, increase the detection difficulty. Zhao *et al.* [25] proposed a two-level labeling technique to solve the above-mentioned problem based on superpixels. The pixels are clustered into superpixels, then, superpixels are clustered into subregions, the superpixel boundaries are updated iteratively until pixels with similar visual senses are clustered into one superpixel, and subregions after many rounds of growth will converge toward defects. This method achieved an average correct detection rate of 91% when applying on cold strips. Furthermore, Wang *et al.* [26] proposed an entity sparsity pursuit (ESP) method to detect surface defects. The defect image can be segmented into several superpixels to realize ESP of defects, while defects do not satisfy the sparsity assumption in a pixel level. The ESP method is insensitive to noise and computationally efficient. For the nature of clustering, it is more suitable for defect classification than defect detection.

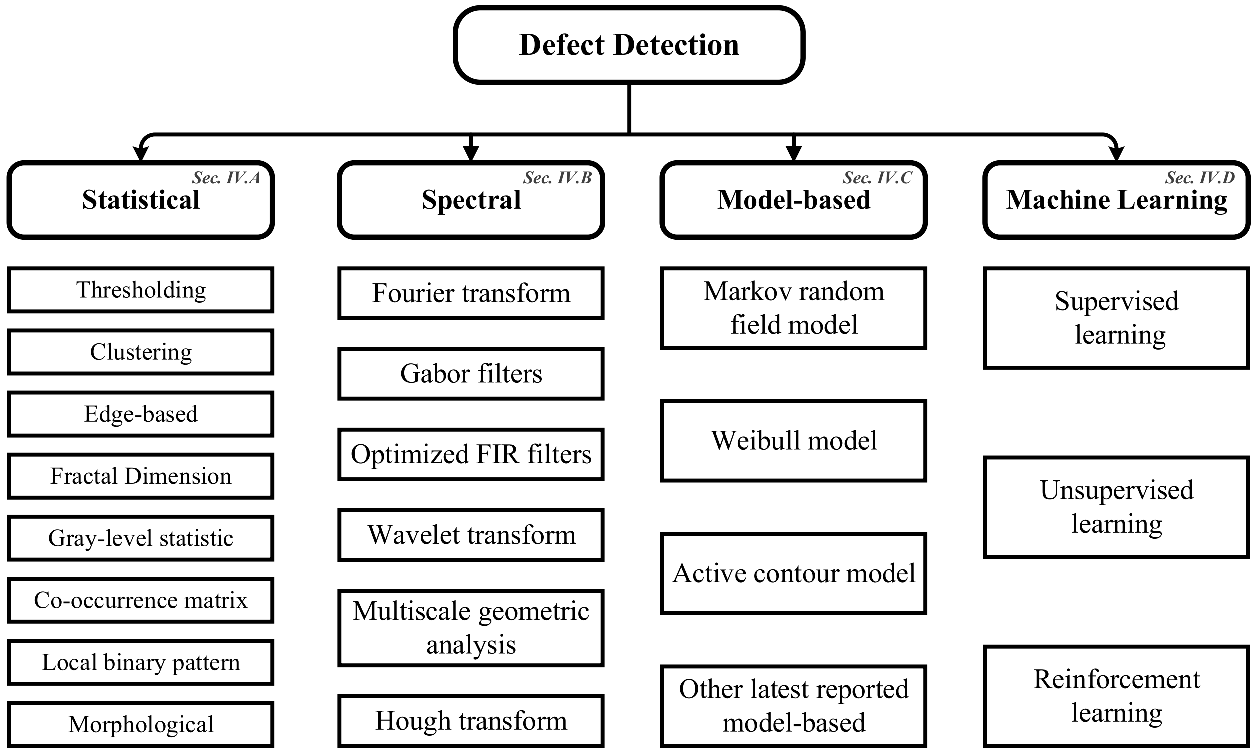


Fig. 3. Overall structure of detection method taxonomy.

3) Edge-Based: The purpose of edge detection is to identify points with obvious brightness changes in digital images. Researchers often use the local image differentiation technique to obtain edge detection operator, and the commonly used edge detection templates for flat steel surface are Kirsch, Sobel, and Canny operator. It is investigated that Sobel is specialized in weighing the influence of pixel position to reduce the ambiguity of edge, but it is sensitive to uneven illumination on flat steel surface, which easily leads to false edge detection. In order to avoid false detection, Borselli *et al.* [27] modified the Sobel operator by applying thresholding to convert the grayscale image into a binary matrix. Furthermore, Shi *et al.* [28] developed eight directional templates to obtain more comprehensive edge information than the original Sobel operator, which only has horizontal and vertical directions. Fig. 4 shows the technical details of these two Sobel operators, including template topology and detect performance. The easily trigged false edge detection was well suppressed by the eight-directional Sobel operator. With the weighted factor and multiple templates, Kirsch is more noise-robust for tiny defect detection among flat steel images, especially suffered from uneven illumination, while the eight directional templates bring large computation amounts to Kirsch. Bo *et al.* [29] simplified the original Kirsch operator by choosing some partial templates on the premise of little influence on edge extraction. Compared with the first-order Kirsch and Sobel operator, Canny possesses better signal-to-noise ratio and detection accuracy due to its second-order feature. However, it suffers from low adaptive ability and sometimes is easy to blur the noise-free region. Hence, it is not a wise choice to directly apply the existing edge detection operator on steel surface

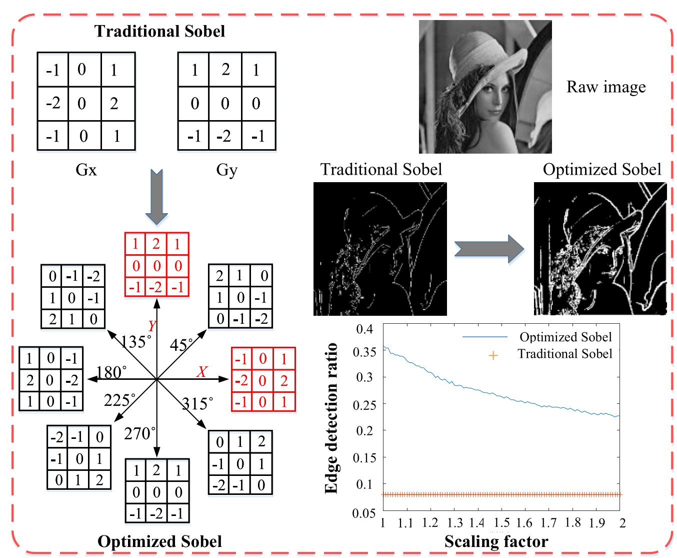


Fig. 4. Comparison of the traditional and the optimized Sobel operator.

defect inspection until the appropriate algorithm is imported to enhance its edge detail retaining ability. Furthermore, many edge detection operators have not been used to detect surface defects of flat steel, such as Prewitt, Laplacian, and Log. Specifically, Prewitt has been used for object enhancement and extraction. Laplacian sharpening template and Log operators have been reported performing well in determining edge position. Thus, it is highly recommended to explore other edge detection operators on the task of steel surface inspection in the near future.

4) Fractal Dimension: Fractal dimension (FD) has the desirable self-similarity, which means that the overall information can be expressed by partial features. It is reported that statistical gray value of defect images practically possesses some features of FD, especially in self-similarity. Zhiznyakov *et al.* [30] employed the fractal features of digital images to detect the defects of flat steel surfaces by characterizing the internal distribution of self-similarity and the image segments with the highest similarity. The experimental results are basically consistent with inspected data from a nondestructive testing inspector. Similarly, the multifractal dimension is utilized by Yazdchi *et al.* [31] to detach and specify the defective region for five typical defects of steel surfaces. It should be pointed out that the application of FD has some limitations because it is only suitable for self-similar defect image detection.

5) Gray-Level Statistic: Using thresholding methods for defect detection directly may be ineffective in low contrast images, so it is necessary to analyze the distribution of image gray level before threshold operation. Yang *et al.* [32] utilized the features (i.e., mean value and distribution of pixels) from steel surface background to separate bright and dark defect objects simultaneously. Furthermore, to be insensitive to noise, Choi and Kim [33] first estimated the distribution of background by a spectral-based approach and then locally refined the defective regions to obtain the probabilistic estimation. This method is superior to the previous defect detection methods and gives the robust results even in a noisy environment. However, the above-mentioned methods for surface defect detection are limited by application scenarios due to the diversity of surface defects. Ma *et al.* [34] proposed a neighborhood gray-level difference method using the multidirectional gray-level fluctuation, which combined the advantages of global and local characteristics. The proposed algorithm not only enhances the generalization but also improves the accuracy of surface defects inspection.

6) Co-Occurrence Matrix: Gray level co-occurrence matrix (GLCM) is a common means to describe the texture by studying the spatial correlation of gray level. Haralick *et al.* [35] first presented GLCM, and the matrix is defined according to the spatial relation between the adjacent pixels of the input image; then, based on the GLCM, 14 texture descriptors (i.e., angular second moment, contrast, correlation, entropy, variance, sum of average, sum of variance, inverse difference moment, variance of difference, sum of entropy, difference of entropy, shadow of clustering, prominence of clustering, and maximal probability) are generated to successfully describe the relationship between the adjacent pixels in an image by calculating the angular relations and distances between the adjacent resolution units. Fig. 5 shows the direction analysis of GLCM with a simple example. Subsequently, GLCM has shown powerful ability on automatic texture discrimination in [36]–[38]. However, it is not an easy job to balance the matrix performance and the window size. In order to overcome the local-descriptive limitation of GLCM, Wang *et al.* [39] combined the complimentary feature sets of the histogram of oriented gradient (HOG) and GLCM to describe the global and local textures of steel surface images, respectively. However, this approach is sensitive to background noises and ununiform gray level changes. Moreover, the computation is relatively complex. Thus, Tsai *et al.* [40] used the weighted eigenvalue of GLCM as a single discriminative feature, so low computational complexity and considerable robustness to noise were achieved simultaneously. Nevertheless, there might be some potential but useful discriminative features in GLCM, which could be explored for future texture analysis. Furthermore, lots of other types of features extracted by some descriptors are suggested to be fused with those of GLCM, and smoothed local binary pattern (SLBP) [41] is a typical example of this method. If so, more descriptive feature vectors can be built for better surface defect recognition of flat steels.

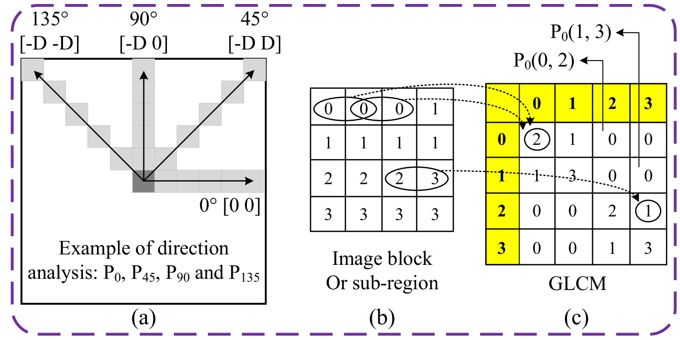


Fig. 5. (a) Direction analysis. (b) Image block. (c) GLCM of P_0.

7) Local Binary Pattern: As a classical operator, local binary pattern (LBP) is widely used to characterize the local texture features of images, which has significant advantages of rotation and gray invariance. In 1994, LBP is first proposed by Ojala *et al.* [42], Later, LBP is frequently used to detect defects on flat steel surface [43]–[45]. In order to overcome the shortcomings of the original LBP (i.e., weak global descriptive and noise sensitive), various LBP variants are developed based on changing the threshold or scale of the original LBP (see Fig. 6), and these variants are widely applied on defect detection of flat steel surface. For example, Wang *et al.* [26] proposed an LBP-inspired feature extractor by estimating the variations of four directions simultaneously, which are horizontal, vertical, and two diagonal directions, so that the features extracted by this method have better visual discrimination. Still, the noise sensitive has not been eliminated for this method. Song and Yan [2] designed an adjacent evaluation completed LBP (AECLBP) by replacing the central pixel with its neighbor pixels. and claimed that AECLBP had achieved considerable recognition accuracy and great robustness to noise. However, its scale adaptability is not so preeminent as it inherits the nature of CLBP. Furthermore, Chu and Gong [41] proposed a novel LBP version called SLBP; fusing the SLBP frames and GLCM, this method can not only suppress noise effectively but also extract features with scale, rotation, illumination, and translation invariance. Nevertheless, descriptive information among nonuniform patterns has been ignored in all these LBP variants. Using reverse thinking, Luo *et al.* [3] proposed a generalized completed LBPs (GCLBP) by first exploring the nonuniform patterns to

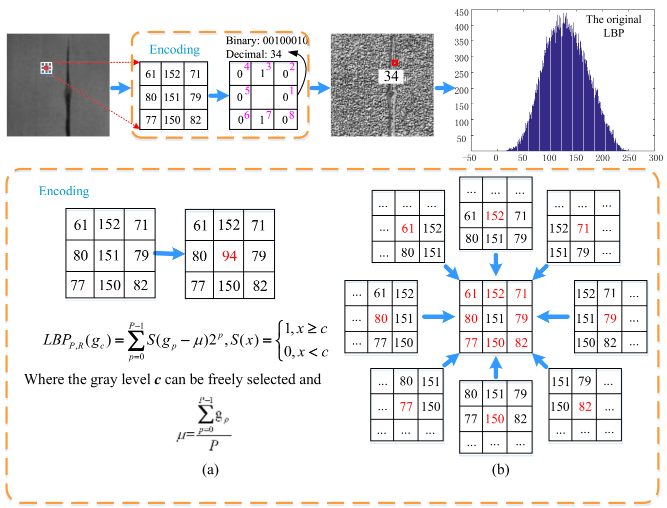


Fig. 6. Standard pipeline of original LBP and the variants of LBP based on changing threshold and scale. (a) LBP extension method based on changing threshold. (b) LBP extension method based on varying scale.

supplement the descriptive information in uniform patterns. Furthermore, the work of GCLBP, Luo *et al.* [46] developed a more effective LBP-descriptor (namely SDLBP), which has remarkable advantages in anti-interference and simplicity of calculation. As a lightweight feature descriptor, LBP variants can be applied on both defect detection and classification, and developing more noise-robust and scale-invariant LBP variants or LBP-like descriptors is highly encouraged and coincides with the AVI future trends.

8) Morphological: Mathematical morphology is an arithmetical tool for image analysis based on morphological structural elements. It has a huge influence on the theory and technology of image processing, especially on shape and structure analysis, which has been widely applied in noise removal [47], [48], feature extraction [49], [50], and image enhancement [51], [52]. Mathematical morphology is specialized in edge processing for its capability of global description. Song *et al.* [53] removed the edges of oil pollution interference and reflective pseudodefect by fusing dilation and erosion operations into image subtraction operations. Furthermore, this research team [25] utilized morphology subtraction to extract the0 defect edges from the industrial liquid region on the steel surface in the cold rolling process. With the firm and complete theory basis, mathematical morphology is widely used in nearly all aspects of image processing, including image segmentation, feature extraction, edge detection, image filtering, image enhancement, and so on. Nevertheless, the calculation expenses when using morphology should be highly emphasized in the online application of surface defect detection for flat steels, as it mainly relies on a so-called structural element probe to traverse the pixels on image for collecting image information, but such operation will generate a large amount of calculation.

9) Brief Summary: Tables I and II give a quick glance for these eight types of statistical methods. In summary, these methods are based on two kinds of fundamental structural properties, regularity and local orientation (anisotropy), and both properties have great perceived value. Chetverikov and Hanbury [54] analyzed and compared these two approaches comprehensively and then concluded that the approaches presented earlier support and complement each other in a natural and understandable way.

B. Spectral

Although the statistical approaches occupy the largest amount of works for steel surface detection in this context, many of them fail to yield reliably correct detection results for several defects with subtle intensity transitions (such as thin roll marks and tiny scratches), especially when illumination varies or pseudodefect visits frequently. Consequently, emergent AVI methods are highly expected for steel surface defect detection in real-world production. Early report about AVI system for hot steel slabs [55] has recommended that it may be possible to find better solutions in the transform domain which are less sensitive to noise and intensity variations than the direct processing methods in the pixel domain, which will be reviewed in Sections III-B1–III-B7.

1) Fourier Transform: With the appearance of the Fourier transform (FT), image features of translation invariance, expansion invariance, and rotation invariance are realized. Generally, the defect images obtained directly from the steel production line need to be further processed to effectively enhance the quality of images. For removing the background noise, Yazdchi *et al.* [31] adopted a temporal Fourier analysis to eliminate the black and white vertical strips in the images formed by the steel plate reflecting ambient light, which appears as the band near a single direct current (dc) term. Similarly, to detect longitudinal cracks from complicated backgrounds on con-casting slab surfaces, the Fourier amplitude spectrum of each subband is computed to get features with translational invariance [56]. Inspired by discrete FT, Aiger and Talbot [57] proposed an unsupervised method based on phase-only transform (PHOT), which can persist only irregular patterns to present defects. This novel approach is shown to be effective and generic on various textured surfaces (i.e., wood, steel, ceramic, and silicon wafers). Nevertheless, the FT-based approaches are inadequate under the circumstances that Fourier frequency components related to the background and defect areas are highly mixed together. This is because it is difficult to implement noninterference each other during processing frequency domain components associated with background or defect respectively.

2) Gabor Filters: FT represents an image by obtaining global features in the frequency domain, and thus, most of local descriptive information is ignored in the spatial domain. This shortcoming is implicitly but markedly made up by Gabor filters in both the spatial and frequency domains by modulating a specific Gaussian kernel function on a sinusoidal wave with a certain frequency [58]. Then, localized and oriented frequency analysis can be achieved by using a simple 2-D Gabor filter [59]. For the targeted task of surface defect detection for flat steels in this article, Gabor function should be chosen carefully because it significantly affects spatial localization, orientation selectivity, and spatial frequency characterization [60], [61]. Fig. 7 shows a classical example of using Gabor filters to detect defect edges.

TABLE I
LIST OF SOME OF TYPICAL STATISTICAL METHODS OF DEFECT DETECTION

Ref.	Year	Methods	Applications	Objects	Difficulties	Image source	Performance
[19]	2008	Fixed threshold	Hot-rolled strip	Multi-type defects	Uneven illumination	Raw images	TPR = 0.929 FPR, FNR, T = NA
[20]	2008	Double threshold and Hough transform	Steel sheet	Multi-type defects	Complex texture characteristics	Database (PRI)	TPR = 0.868 FPR, FNR, T = NA
[22]	2014	Histogram thresholding	Hot-rolled steel	Multi-type defects	Uneven illumination	Raw images	All not given
[23]	2017	Global Adaptive Percentile Thresholding	Hot-rolled steel	Blister defect water-deposit	Size uncertainty	Database (PRI)	TPR = 0.942 FPR = 0.026 FNR = 0.155 T: = NA
[63]	2017	Double threshold	Steel plates	Multi-type defects	Surface noise and uneven defect positions	Raw images	TPR = 0.88-1.00 FPR = 0.00-0.15 FNR, T = NA
[64]	2017	Double threshold	Steel slab	Pinhole	Small size and pseudo-noise interference	Raw images	TPR = 0.962 FPR = 0.0131 FNR, T = NA
[24]	2012	Clustering Algorithm	Hot-rolled strip	Periodically defects	Complex texture characteristics	Raw images	F-Measure: 0.86 TPR, FPR, FNR = NA T = NA
[25]	2016	Two-level labeling technique	Cold-rolled strip	Cracks scratches	Pseudo-noise interference	Raw images	TPR = 0.91 FPR, FNR, T = NA
[26]	2019	LBP-spired and superpixel segmentation	Hot-rolled plates	Multi-type defects	Pseudo-noise interference	Database (PUB)	FPR = 0.088, FNR = 0.266, MAE = 0.143 TPR, T = NA
[27]	2010	Sobel method	Flat steel	Inclusions rolled in defect	Complex texture characteristics	Database (PRI)	TPR = 0.87 FPR, FNR, T = NA
[31]	2009	Multifractal Dimension and Temporal Fourier transformation	Cold-rolled mill	Multi-type defects	Defects with irregular shapes	Database (PRI)	TPR = 0.979 FPR, FNR, T = NA
[39]	2017	HOG and GLCM	Steel surface	Distributed defects: scale	Complex texture characteristics	Raw images	TPR = 0.909 T: 19.79 ms per image FPR, FNR = NA
[41]	2015	SLBP and GLCM	Strip steel	Multi-type defects	Random noise and uneven illumination	Database (PRI)	TPR = 0.916±0.02 T: 7.45 ms per image FPR, FNR = NA
[2]	2013	Adjacent evaluation completed local binary patterns (AECLBPs)	Hot-rolled strip	Multi-type defects	The variations of the intra-class changes, the illumination and grayscale changes	Database (PUB)	TPR = 0.989±0.37 FPR, FNR, T = NA
[50]	2011	Gabor and morphological	Steel slab	Pinhole	Small size and uneven illumination	Raw images	TPR = 0.871 FPR = 0.038 FNR, T = NA
[52]	2016	Genetic algorithm and mathematical morphology	Strip steel	Multi-type defects	Non-uniform illumination	Database (PRI)	T: 7.48 ms per image TPR, FPR, FNR = NA

Notes:
Image source.
PUB: Public, PRI: private

Performance criteria.
TPR: True positive rate, FPR: False positive rate, FNR: False negative rate, MAE: Mean absolute error, T: Detection time

This point has also been emphasized more than once during the Gabor feature extraction process when it was used for defect detection of flat steel products [50], [62], [63]. It is well recognized that the real and imaginary parts can be, respectively used, for image smoothing and edge detection for a typical Gabor detector. The parameters of the Gabor filter are mainly decided by the defect size and direction, and it is thus hard to obtain the desired results for miscellaneous defects with various sizes by a single Gabor filter. Accordingly, Choi *et al*. [64] proposed a two- Gabor-filter combinational method enhanced by morphological features separate pinholes on steel slabs. Similarly, Medina *et al.* [65] claimed that the correct defection rate could be increased by fusing Gabor features to other classical image features to a large extent. It was also drawn in [65] that real-time aspect should be attached great importance to on-site application of defect detection for industrial manufacturing. The detection acceleration method by employing the Log-Gabor filter bank presented in [66] provides a typical case about this assertion. The above-mentioned methods have proven that Gabor filtering performs well on

TABLE II
STRENGTHS AND WEAKNESSES OF DIFFERENT STATISTICAL METHODS OF DEFECT DETECTION

Taxonomy	Methods	Strengths	Weaknesses
Statistical	Thresholding	Simple, easy to understand and implement.	Fail to detect the defect with little difference from background.
	Clustering	Robust to noise and with high computational efficiency.	Easy to be disturbed by pseudo defects such as industrial water droplets.
	Edge-based	Can extracted some low-order features of the image and easy to realize.	Susceptible to noise and only suitable for images with low resolution.
	Fractal Dimension	The overall information of images can be expressed by partial features.	Detection accuracy is unsatisfactory and have limitation on images without self-similar.
	Gray-level statistic	Suitable for low resolution images.	Low timeliness and no automatic threshold selection.
	Co-occurrence matrix	The spatial relation of extracted image pixels is complete and accurate.	Computation and memory requirements are relatively high.
	Local binary pattern	Can quickly extract discriminative features with rotation and gray invariance.	Scale change and noise have a great influence
	Morphological	Highly suitable for random or natural textures and computationally simple.	Only suitable for aperiodic image defects

characterizing distinctive texture patterns. Besides, Gabor can be combined with statistical methods to get better results (such as LBP, GLCM, and fractal), and Alvaro *et al.* [67] confirmed that the combinational approach based on Gabor filter and volumetric FD possesses promising ability of obtaining rich texture features.

3) Optimized FIR Filters: The filter optimization process is essential to effectively separate the frequencies of the defect-free texture with low signal energy and the defective texture with high signal energy [68]. As a typical optimized filter, the finite impulse response (FIR) filter provides relatively preeminent feature separation between the defect-free and the defective regions from the FIR-filtered frames [8]. Kumar [69] pointed out in his Ph.D. dissertation that FIR filter performs better both on optimization scale and computational expense than infinite impulse response (IIR) and Gabor filters as FIR filter has more freely available turning parameters. Furthermore, Kumar and Pang [70] and Kumar [71] applied the FIR filters on the fabric defect detection and obtained milestone achievement in textile industry. Inspired by this trend, Jeon *et al.* [72] proposed a novel suboptimal FIR filtering scheme that adaptively combines the optimized FIR filters by considering the texture features of images captured from a dual-light switching-lighting device, to detect various shapes of defects on steel surfaces. This innovative detection method is effective to handle nonuniform surfaces and scale-oxidized substances caused during the hot-working manufacturing process. In addition, FIR filters are very suitable to be embedded in FPGAs, which is compliant with the lightweight trend of the instrumentation and measurement society. To sum up, optimized FIR filtering shows enormous application potentiality in the detection of defects for flat steel surfaces.

4) Wavelet Transform: Compared with Gabor filters, wavelet transform can not only move the time–frequency window but also automatically adjust the window with the change of the frequency in the center of the window. Meanwhile, the characteristics of wavelet are more in line with the human visual mechanism. Consequently, wavelet transform can effectively extract information from signals and perform multiscale analysis of functions or signals through scaling and shifting operations. Due to the existence of pseudo-defects caused by water droplets, oxidized scales, uneven illumination, and so on, the defect detection of steel surface becomes increasingly challenging. Five different types of wavelets, namely, Haar, Daubechies 2 (DB2), Daubechies 4 (DB4), biorthogonal spline (Bior), and multiwavelet, have been evaluated by Ghorai *et al.* [1] to extract the features of small-size image blocks. However, the antinoise measure resisting the uneven illumination is absent in this scheme. Liu and Yan [73] proposed a novel wavelet-based image filtering algorithm based on anisotropic diffusion. The features of anisotropic diffusion encouraging the intraregion smoothing adaptively and inhibiting the interregion diffusion permit that wavelet anisotropic diffusion method can not only extract defect from noisy backgrounds reliably but also can separate high- and low-frequency components effectively. Similarly, Wu *et al.* [74] proposed an undecimated wavelet transform (UMT) for solving the problem of false alarms resulted from oxidized scales and watermarks with an overall recognition rate of 90.23%. Besides the challenge of pseudodefects, some steel surface defects produce very subtle intensity transitions. Song *et al.* [75] employed a scattering convolution network (SCN) based on wavelet transform to improve the tolerance ability on local and linearized deformations. This method has been successfully applied on surface defect detection for hot-rolled strips and obtained an average correct recognition accuracy of 97.22%.

5) Multiscale Geometric Analysis: The singularity of 2-D defect images captured from steel production lines is primarily depicted by edge information that appears as irregular lines or surfaces. Wavelet transform can optimally characterize the point singularity but can hardly characterize the lines and surface singularities due to the finiteness of separable wavelet directions. An appropriate solution to this problem is to employ multiscale geometric analysis (MGA) whose multidirectivity renders protection and detection of edge features (especially singular edges) more precisely. Generally, MGA methods are separated into adaptive and nonadaptive types. The adaptive methods are represented by Bandelet [76] and Tetrolet [77]. Zhang *et al.* [78] have proposed an image fusion method based on Bandelet-pulse coupled neural network (PCNN) model to solve the problem of the pseudo-Gibbs phenomena around singularities. For quality assurance of con-casting slabs and hot strips, Xu *et al.* [79] successively proposed a Shearlet-based feature extraction method (DST-KLPP) and an adaptive MGA method (RNAMlet) [80], and both of them emphasized much on detection rates and computation expenses. When it comes to the typical nonadaptive MGA such as Ridgelet [81] and Curvelet [82], Ai and Xu [56] applied Curvelet enhanced by kernel locality preserving projections to track longitudinal cracks on con-casting slabs. Nevertheless, how to effectively distinguish confused defect edges and active background textures is still an open research topic for both engineering and academia.

6) Hough Transform: Hough transform (HT) [83] is considered as a powerful tool in well-defined line-feature detection. Its applications can be found in the fingerprint identification [84], [85] and vehicle license plate recognition [86]. Interestingly, Sharifzadeh *et al.* [20] applied HT to detect the defects of holes, scratches, coil breaks, and rusts on cold-rolled steel strips. However, it is difficult to raise the correct detection rates to more than 90%. Hough line detection has the advantage of strong anti-interference ability and is also insensitive to noises, incomplete part of edges, and other coexisting nonlinear structures. However, HT can only track the direction of edges, and the length information of the line segment is lost. It is worth noting that the time and space complexity should be effectively reduced if using HT for surface defect detection of flat steels.

7) Brief Summary: Tables III and IV give a quick glance for these six types of spectral methods, and the advantages and disadvantages are also analyzed briefly. In general, spectral methods are dedicated to find a special transform domain where the defect objects can be more easily and completely separated from both the local and global backgrounds.

C. Model-Based

Naturally, statistical-based methods are relatively sensitive to noise, while spectral-based methods lack local information, and both of them have bottlenecks on representing miscellaneous defects and stochastic background variations appeared on textured surfaces. Model-based methods tend to perform better for diverse defect detection by projecting original texture distribution of image blocks to low-dimensional distribution via a structurally special model enhanced by parameter learning. Several model-based methods are now briefly discussed next.

1) Markov Random Field Model: On the basic idea of that a texture has interaction among relevant random variables in a stochastic or periodic 2-D field, Cross and Jain [87] first used Markov random field (MRF) as texture model, and the structure of 2-D MRF can well represent the spatial correlation of image pixels. Inspired by this concept, Gayubo *et al.* [88] utilized MRF to restore flat steel defects (i.e., cracks) and eliminate the spurious features (i.e., pseudo). Furthermore, Xu [89] dramatically decreased the detection false rate from 18.8% to 3.7% by using the proposed context-adaptive hidden Markov tree model (CAHMT) based on an assertion that the correlation of wavelet coefficients of flat steel surface images at different scales satisfies the Markov property. The recent works exhibit the huge application potentiality of MRF on industrial surface defect detection.

2) Weibull Model: Some flat steel surface defects that produce subtle intensity transitions may be difficult to be detected by using the above-mentioned MRF-based method. A potential solution to handle the detection task of such defects is to utilize the relatively complete descriptive superiorities on texture contrast, scale, and shape of Weibull distribution [90]. Continuing this idea, Fofi *et al.* [16] proposed a novel, nonparametric and efficient Weibull-based defect detection method by computing two parameters of a Weibull fit for the distribution of image gradients in local regions. This unsupervised method performs well on a large industrial optical inspection database, which involves some highly challenging flat steel defects. However, it is hard for Weibull distribution to handle the defects with gradual intensity or with low contrast. Hence, Liu *et al.* [91] developed a Haar–Weibull-variance (HWV) model by replacing the features of local gradient magnitude by Haar features from local patches. This method is reported to have achieved an average correct detection rate of 96.2% on a homogeneously textured defect data set gathered from an actual hot-rolling mill.

3) Active Contour Model: The basic idea of active contour model (ACM) is to use a continuous curve to express and locate the edge of object (here is, defect) by curve evolution. ACM is popular in image segmentation as it can achieve subpixel accuracy of object boundaries [92], [93]. Song and Yan [94] proposed saliency convex ACM (SCACM) by fusing visual saliency map into convex energy minimization function to detect micro surface defects on silicon steel strips. The SCACM yielded good performance on both spot defect and steel pit defect as the fused visual saliency map highlights the potential defects and suppresses the clutter background as well. Yang *et al.* [95] developed an ACM-based defect detection method without edges through incorporating a variable penalty term and a convolution kernel and reported that it can effectively segment defect features with inhomogeneous boundaries from complicated surface textures. The iteration steps and computing time increasingly attract the attention of scholars.

4) Other Latest Reported Model-Based: There are some latest reported model-based defect detection methods. Susan and Sharma [96] proposed the Gaussian mixture entropy model for defect detection, which is specialized in identifying miscellaneous defects, such as holes and stains. Based on low-rank representation, Yan *et al.* [97] utilized smooth-sparse decomposition (SSD) model for anomaly

TABLE III
LIST OF SOME OF TYPICAL SPECTRAL METHODS OF DEFECT DETECTION

Ref.	Year	Methods	Applications	Objects	Difficulties	Image source	Performance
[31]	2009	Multifractal Dimension and Temporal Fourier transformation	Cold-rolled mill	Multi-type defects	Defects with irregular shapes	Database (PRI)	TPR = 0.979 FPR, FNR, T = NA
[56]	2013	Fourier transform	Continuous casting slabs	Longitudinal cracks	Complex texture characteristics	Raw images	TPR = 0.919 FPR = 0.0893 FNR, T = NA
[50]	2011	Gabor and morphological	Steel slab	Pinhole	Small size and uneven illumination	Raw images	TPR = 0.871 FPR = 0.038 FNR, T = NA
[62]	2015	Gabor filtering	Thick plates	Periodic defects	Non-uniform illumination	Raw images	TPR = 1.00 FPR = 0.0075 FNR, T = NA
[63]	2017	Double threshold	Steel plates	Multi-type defects	Surface noise and uneven defect positions	Raw images	TPR = 0.88-1.00 FPR = 0.00-0.15 FNR, T = NA
[64]	2017	Double threshold	Steel slab	Pinhole	Small size and pseudo-noise interference	Raw images	TPR = 0.962 FPR= 0.0131 FNR, T = NA
[66]	2011	Log Gabor filter bank	Flat surfaces	Products on homogeneous flat surface	Complex texture characteristics	Database (PUB)	TPR = 0.998 FPR, FNR, T = NA
[72]	2015	Optimized general-finite impulse-response filter	Steel plate	Multi-type defects	Non-uniform brightness and various shaped defects	Database (PRI)	TPR = 0.979 T: 106 ms per frame FPR, FNR = NA
[1]	2012	Wavelet feature sets and VVRKFA	Hot-rolled steel	Multi-type defects	Large surface, variation in appearance, and their rare occurrences	Database (PRI)	G-mean: 93.8%, F-measure: 90.4% T: 86.5 ms per image TPR, FPR, FNR = NA
[73]	2014	A novel wavelet-based image filtering algorithm	Cold-rolled strip	Multi-type defects	The complexity of surface texture	All not given	All not given
[74]	2008	Undecimated Wavelet Transform	Hot-rolled plates	Horizontal crack	Pseudo-noise interference and uneven illumination	Database (PRI)	TPR = 0.902 FPR, FNR, T = NA
[75]	2014	Cascading wavelet transforms	Hot-rolled strip	Multi-type defects	Local deformation	Database (PUB)	TPR = 0.986±0.59 FPR, FNR, T = NA
[78]	2012	Bandelet-PCNN	Strip steel	Multi-type defects	Pseudo-Gibbs phenomena around singularities	All not given	All not given
[79]	2015	Shearlet transform	Continuous casting slabs, hot-rolled steels, and aluminum sheets	Multi-type defects	Complicated background, pseudo-defects interference, low contrast and small size	Database (PRI)	TPR = 0.944, 0.956 and 0.925, for three types of flat steel FPR, FNR, T = NA
[80]	2018	RNAMlet	Continuous casting slabs, hot rolled steel plates and cold rolled steel strips	Multi-type defects	Different surface appearances and different speeds of movement	Database (PRI)	TPR = 0.885, 0.972 and 0.984, for three types of flat steel FPR, FNR, T = NA

Notes:
Image source.
PUB: Public, PRI: private

Performance criteria.
TPR: True positive rate, FPR: False positive rate, FNR: False negative rate, MAE: Mean absolute error, T: Detection time

detection in images, Huangpeng *et al.* [98] proposed a novel weighted low-rank reconstruction model for automatic visual defect detection, and Zhou *et al.* [99] presented a double low-rank and sparse decomposition (DLRSD) model to obtain the defective region of steel sheet surface. These approaches are reported to perform well. Wang *et al.* [26] constructed a compact model to be regarded as a kind of guidance information by mining intrinsic image priors, and it offers a good generalization ability for different detection tasks and is sufficiently robust to noise. Furthermore, Wang *et al.* [17] proposed a guidance template-based defect detection method for strip steel surfaces by introducing a sorting operation to sort gray levels with each column of test image and then subtracts the sorted test image with guidance template to locate defects conveniently. It achieved an average detection rate of 96.2% on a data set with 1500 test images involving

TABLE IV
STRENGTHS AND WEAKNESSES OF DIFFERENT SPECTRAL METHODS OF DEFECT DETECTION

Taxonomy	Methods	Strengths	Weaknesses
Spectral	Fourier Transform	Invariance to translation, expansion and rotation.	Difficult to realize non-interference when dealing with frequency-domain components related to background or defect.
	Gabor Filters	Suitable for high dimensional feature space with low computational burden.	Hard to determine the optimal filter parameters and no rotation invariance.
	Optimized FIR Filters	Suitable for defects with subtle intensity variation and more free parameters to keep the computational simplicity.	Limitations to solve the problem of low frequency.
	Wavelet Transform	Suitable for multi-scale image analysis and can compression image efficiently with less information loss.	Easily to be affected by feature correlations between the scales.
	Multiscale Geometric Analysis	Suitable for the optimal and sparse representation of high-dimension data. Good at image processing of strong noise background.	Exist redundancy problem.
	Hough Transform	Strong anti-interference ability and insensitive to noise.	Only detects defects of specific shapes (i.e., lines, circles and ellipses).

challenges of uneven illumination. Any information descriptive models with low computational complexity can be considered for the task of surface defect detection for flat steels in the future.

5) Brief Summary: Table V highlights some representatives of model-based detection methods, and the strengths and weaknesses are also gathered in Table VI. In this branch direction, how to found noise robust, theoretically explainable, computationally simple models to adaptively absorb sparse features of defects will attract increasing attention from both academia and industry.

D. Machine Learning

The essence of machine learning is to analyze and learn data and then make decisions or predictions accurately for further operation. With the popularity of artificial intelligence in recent years, machine learning, a powerful branch of model-based methods, has been proposed extensively for defect detection of flat steel surface. As shown in Fig. 8, the defect detection task is essentially handled as a binary (defective or defect-free) classification problem in machine learning methods (or we can call them advanced classifiers), and the machine learning defect detection methods are reviewed in three categories of supervised, unsupervised, and reinforcement learning.

1) Supervised Learning: The goal of supervised learning is to model a conditional distribution between input vectors (surface images) and target vectors (defect label 0 or 1). Support vector machine (SVM), decision trees, and neural networks are classical examples in this category. As a generalized linear classifier for binary classification of data, SVM is frequently utilized to identify the defective and defect-free regions [100], [101]. Ghorai *et al.* [1] hold that the performance of classifiers in defect detection depends on the feature and classifier combination and fused the classifiers (i.e., SVM and VVRKFA) with different feature sets (i.e., Haar, DB2, and DN4) to divide the test images into defective and normal ones, finding that the performance of VVRKFA with one-level Haar features ranks first among all the feature-classifier combinations. The neural network can learn the pattern from the training data set and determine the category of the new data according to the previous knowledge. Liu and Kang [102] used a two-layer feedforward neural network to classify the pixel of test images into defect and defect-free regions on the basic idea that the defect detection task is actually a binary classification problem. However, a great quantity of parameters of neural networks leads to huge computational complexity. Convolution and subsampling in the convolution neural network (CNN) effectively reduce the model size by tailoring the model parameters. Thus, CNN-based architectures are widely applied to automatic feature extraction [103] as well as on image defect detection [104]–[108] in industrial inspection. For example, Cha and Choi [105] proposed a deep CNN to detect cracks on concrete and steel surface without calculating defect features. The framework can effectively resist the interferences caused by the extensively varying real-world situations. This team also designed a structural visual inspection method based on faster region-based CNN (faster R-CNN) to ensure quasi-real-time simultaneous detection of multiple types of defects [109]. Moreover, Song *et al.* [108] realized the precise detection of weak scratches on metal surface by confusing deep CNN and skeleton extraction, and the experimental results indicate its strong robustness to background noises. In order to enable CNN-based detection methods to be applied in real-time industrial scenes, an impressive method called you only look once (YOLO) network was proposed by addressing the biclassification task as a regression problem. Li *et al.* [110] improved the YOLO network by making it all convolutional and then applied the YOLO-variant to detect surface defects of flat steel, and this network reached 99% correct detection rate with a speed of 83 FPS on a data set of 4655 defect images of cold-rolled steel surface. The satisfactory detection performance of supervised learning methods is achieved only with a premise of having a great quantity of labeled image samples on defect database, while collecting and labeling a great number of image samples on industrial manufacturing line are quite labor-intensive and time consuming, or even to say, impracticable.

2) Unsupervised Learning: Automated defect detection has always been a challenging task, especially in actual

TABLE V
LIST OF SOME OF TYPICAL MODEL-BASED METHODS OF DEFECT DETECTION

Ref.	Year	Methods	Applications	Objects	Difficulties	Image source	Performance
[88]	2006	Markov random field model	Sheet-metal	Split defects	Remaining spurious features	All not given	All not given
[89]	2013	Hidden Markov tree	Steel strips	Multi-type defects	Complex texture characteristics	Database (PRI)	TPR = 0.944 FNR = 0.037 FPR, T = NA
[16]	2013	Weibull distribution	Steel surface	Multi-type defects	Arbitrary deviations of the reference texture	Database (PRI)	EER: 3.2%, AUC = 0.99 FNR = 0.051 TPR, FPR, T = NA
[91]	2017	Haar-Weibull-Variance model	Steel strips	Multi-type defects	Miscellaneous patterns, low contrast and Pseudo-noise interference	Database (PRI)	TPR = 0.962 T: 52 ms per image FPR, FNR, T = NA
[94]	2013	Saliency convex active contour model	Silicon Steel Strip	Spot-defect Steel-pit-defect	Micro defects in the cluttered background	All not given	All not given
[95]	2018	Active contour model	Large steel roller	Speckles Chatter marks Feed traces	Large dimension and weight	All not given	All not given
[99]	2018	Double Low-Rank and Sparse Decomposition Model	Hot-rolled strip	Multi-type defects	Noise and uneven illumination	Database (PUB)	AUC: 0.8350, MAE: 0.1584, T: 171.3 ms per image TPR, FPR, FNR = NA
[26]	2019	Compact model	Hot-rolled plates	Multi-type defects	The interference of pseduo-defects	Database (PUB)	FPR=0.088, FNR=0.266, MAE=0.143 TPR, T = NA
[17]	2019	A unique guidance template	Steel strips	Multi-type defects	Defects with miscellaneous patterns	Database (PRI)	TPR = 0.962 T: 35 ms per image FPR, FNR = NA

Notes:
Image source.
PUB: Public, PRI: private

Performance criteria. TPR: True positive rate, FPR: False positive rate, FNR: False negative rate, EER: Equal error rate, AUC: Area under curve, MAE: Mean absolute error, T: Detection time

TABLE VI
STRENGTHS AND WEAKNESSES OF DIFFERENT MODEL-BASED METHODS OF DEFECT DETECTION

Taxonomy	Methods	Strengths	Weaknesses
Model-based	Markov Random Field Model	Can be combined with statistical and spectral methods for segmentation applications to capture the local texture orientation information.	Cannot detect small defects. Not suitable for global texture analysis. Strong spatial constraint.
	Weibull model	Has superiorities on describing the contrast, scale and shape of textures.	Hard to detect defects with gradual intensity or with low contrast.
	Active contour model	Can achieve sub-pixel accuracy of object boundaries. Has good performance on both spot-defect and steel-pit-defect.	Hard to calculate the convergence position due to lacking constraints.

industrial application. It is not always easy to gather a large number of labeled image samples, that is, the training images consist of a set of input vectors without any corresponding target values. Here, the unsupervised learning is dedicated to discover groups of similar examples within the input data. In some cases, it is also called clustering.

CNN can be used not only for supervised learning but also for unsupervised learning. The deep convolutional generative adversarial network (DCGAN) [111] is a kind of CNN, which build certain constraints on traditional generative adversarial networks (GANs) to overcome its drawback of unstable output, and it often works in unsupervised learning manner for defect detection [112], [113]. Notably, Zhao *et al.* [113] combined GAN and autoencoder (AE) and LBP to detect defects on a textured surface, which needs only positive samples without any defect sample nor manual label. This framework is of better practical application value due to its unsupervised natures. Moreover, AE-based algorithms also demonstrate strong competitiveness in steel surface defect detection, which are reported to be fairly noise-robust. Mei *et al.* [114] utilized convolutional denoising AE network to reconstruct image patches, combined with the reconstruction residual maps, and

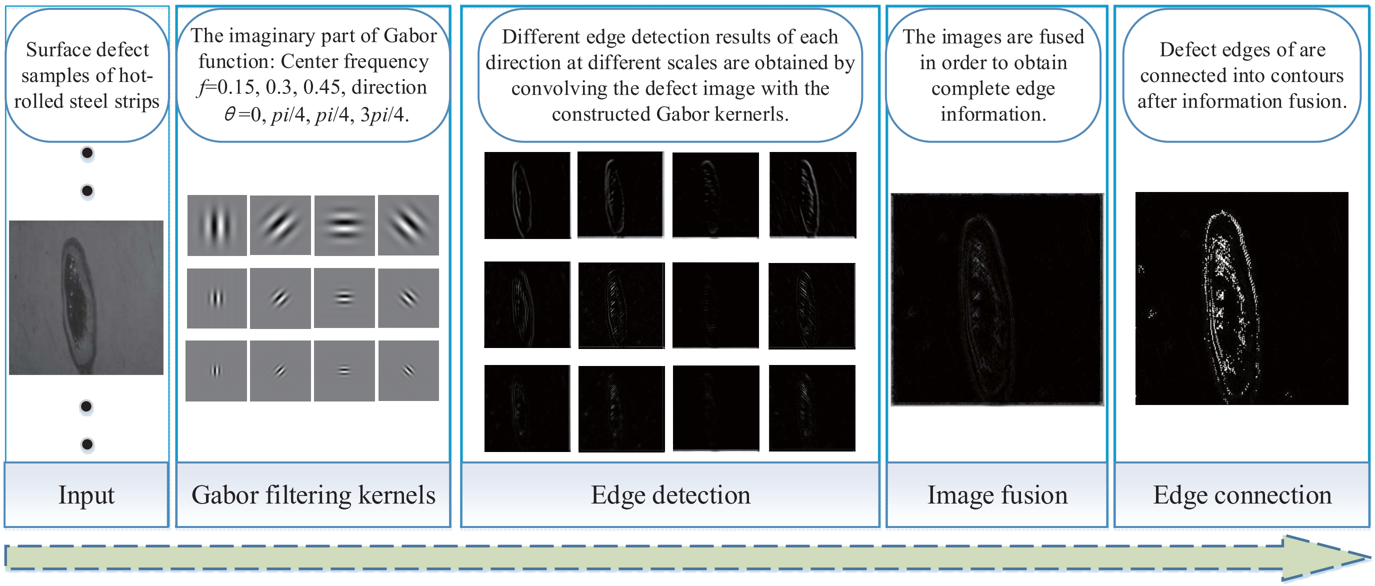


Fig. 7. Example of using Gabor filters to detect defect edges.

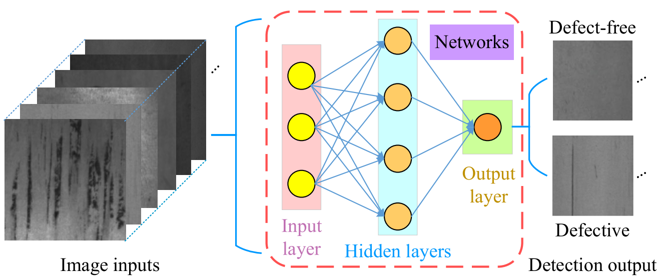


Fig. 8. General flow of machine learning methods.

this scheme can reliably learn the final detection results, where no manual intervention is needed throughout all the detection process. Youkachen *et al.* [18] inventively applied convolutional AE (CAE) to reconstruct the defective test images, and then, the reconstructed images were used to highlight the shape feature by simple postprocessing algorithms, providing another good application case on miscellaneous defect detection through unsupervised learning. Although the abovementioned unsupervised learning methods are able to learn from unlabeled images, they are susceptible to noise and initial value. How to consolidate the abovementioned impressive results into reliable achievements will become the focus of this branch's direction.

3) Reinforcement Learning: Both supervised learning and unsupervised learning methods have obtained a rapid progress on surface defect detection of industrial flat steel. Different from these two methods, the reinforcement learning methods realize surface defect detection with fairly small data sets through a so-called rewards and punishment system to optimize inner parameters automatically. For example, Ren *et al.* [115] proposed a general approach requiring small training data for automated surface inspection and transferred the features from a pretrained deep learning network and convolved the trained classifier over the input images. In the defect detection tests of flat steel surface, the proposed algorithm reduced error escape rates by from 6.00% to 19.00% in three defect types than several state-of-the-art benchmarks. Tao *et al.* [116] proposed a novel cascaded AE (CASAE) framework to detect some complex defects under the industrial environment, which converts test images into pixel-wise prediction mask based on semantic segmentation. The defect regions can be accurately tracked by using a compact CNN. Zhou *et al.* [117] designed a new bilinear model of double-visual geometry group 16 (D-VGG16) to extract global and local features of surface defects, and these features were then fed to the gradient-weighted class activation mapping (Grad-CAM) to finish defect detection. The proposed method can simultaneously realize defect classification and localization with small samples in a weakly supervised manner. Moreover, He *et al.* [4] proposed a new method named CAE-SGAN by fusing CAE and semisupervised GAN (SGAN), where CAE acts as an advanced classifier to identify detective regions. The generalization ability improved by semisupervised learning from SGAN supported that the CAE-SGAN scheme yielded competitive performance compared with some other traditional detection methods.

4) Brief Summary: Supervised learning determines test samples defective or nondefective by training samples with labels. Unsupervised learning can realize accurate and effective surface defect detection through the training of a large number of unlabeled samples in many harsh industrial manufacturing scenarios. In contrast, reinforcement learning tries to obtain intelligent self-optimization through continuously interacting with its environment so as to achieve defect detection by making full use of limited labeled and unlabeled samples at low cost. For ease read, Table VII lists some typical defect detection methods based on machine learning with a short summary closely presented in Table VIII. As stated earlier, machine learning tends to accomplish the defect detection tasks more intelligently, and such an emerging technology

TABLE VII
LIST OF SOME OF TYPICAL MACHINE LEARNING METHODS OF DEFECT DETECTION

Ref.	Year	Methods	Applications	Objects	Difficulties	Image source	Performance
[100]	2014	Gabor filtering and SVM	Steel plates	Seam cracks	Small size and low contrast	Raw images	TPR = 0.945 FNR = 0.003 FPR, T = NA
[1]	2012	wavelet feature sets and VVRKFA	Hot-rolled steel	Multi-type defects	Various appearance and rare occurrences	Database (PRI)	G-mean: 93.8%, F-measure: 90.4% T: 86.5 ms per image TPR, FPR, FNR = NA
[102]	2005	Algorithm based on feed-forward neural network	Cold-rolled strip	Scratches	Complex texture characteristics	All not given	All not given
[105]	2017	A deep CNN	Steel surface	Cracks	Extensively varying real-world situations	Raw images	TPR = 0.974 FPR, FNR, T= NA
[106]	2019	Classification priority network	Hot-rolled steel plates, Hot-rolled steel strips	Multi-type defects	The different morphological characteristics of the same type of defects	Database (PRI)	TPR = 0.94 and 0.96 respectively FPR, FNR, T= NA
[107]	2019	CNN and long short-term memory (LSTM)	Steel Plates	Roll marks	Low contrast in their background	Database (PRI)	TPR = 0.862 TPR, FPR, FNR = NA
[108]	2019	Deep convolutional neural networks (DCNNs)	Metal component surfaces	Weak micro-scratch	Non-uniform gray distribution, various shapes, low contrast in their background	Database (PRI)	IoU = 0.8125 TPR, FPR, FNR = NA T = NA
[110]	2018	Improved YOLO detection network	Cold-rolled strip	Multi-type defects	Diverse and complex features	Database (PRI)	MAP: 97.55% Recall rate: 95.86% Speed: 83FPS TPR, FPR, FNR = NA T = NA
[112]	2017	AnoGAN	Multi-type	Multi-type defects	Small labeled samples	Database (PRI)	TPR = 0.8834 Recall = 0.7277 AUC = 0.89 TPR, FPR, FNR = NA T = NA
[18]	2019	Convolutional auto-encoder (CAE)	Hot-rolled strip	Multi-type defects	Wide variety of forms and various classes	Database (PUB)	All not given
[113]	2018	GAN and autoencoder	Multi-type	Multi-type defects	Hard to collect samples beforehand and manual labelling is time-consuming	Database (PRI)	TPR = 0.985 T: 80.3 ms per image FPR, FNR, T= NA
[114]	2018	Convolutional denoising autoencoder networks	Multi-type	Multi-type defects	Collecting and labeling large amounts of defective samples are usually harsh and impracticable.	Database (PUB)	Recall = 0.6437 TPR = 0.638 F-Measure = 0.6279 FPR, FNR, T= NA
[115]	2018	A Generic Deep-Learning-Based Approach	Hot-rolled strip	Multi-type defects	collecting training dataset is usually costly	Database (PUB)	TPR = 0.992 EER = 0.00 FPR, FNR, T= NA

Notes:
Image source.
PUB: Public, PRI: private

Performance criteria. TPR: True positive rate, FPR: False positive rate, FNR: False negative rate, EER: Equal error rate, AUC: Area under curve, MAE: Mean absolute error, IoU: Intersection over union, MAP: Mean average precision, T: Detection time

is promising in the application of flat steel surface defect detection.

V. SUMMARY AND DISCUSSION

In Tables I, III, V, and VII, some typical defect detection methods among the four big families are highlighted. Attention is drawn to application scenarios, types of defects, involved challenges, source of images under test, and reported detection performance. In terms of detection performance, on the one hand, detection accuracy is an important evaluation criterion. Different references have different standard of detection accuracy, such as true positive rate (TPR), false-negative rate (FNR), false-positive rate (FPR), equal error rate (EER), area under curve (AUC), mean absolute error (MAE), G-mean, F-measure, and so on. On the other hand, running time is another vital evaluation criterion, as the rapid casting or rolling rhythm of flat steel in real-world industrial sites has high-level time cost requirement on defect detection.

TABLE VIII
STRENGTHS AND WEAKNESSES OF DIFFERENT MACHINE LEARNING METHODS OF DEFECT DETECTION

Taxonomy	Methods	Strengths	Weaknesses
Machine Learning	Supervised learning	Has a good and reliable effect.	Dependent on labeled samples, but defective samples of flat steel are limited.
	Unsupervised learning	Require no labeled samples for training.	Susceptible to noise and highly influenced by initial values.
	Reinforcement learning	Require only a small number of labeled samples and the result is stable.	Training requires a lot of interaction and reduces efficiency.

Respect to the image source used for study, the raw images represent the real-world images (always with large size e.g., 4096 × 1024 pixels), which are acquired by an AVI machine running on industrial steel production line for defect detection. While the database includes a number of defective or defect-free image block samples (always with small size, e.g., 256 × 256 pixels), which are obtained from raw images after some postprocesses of segmentation and labeling. It is worth mentioning that the results of detection accuracy evaluated based on raw images are more reliable than those evaluated based on database when the corresponding detection methods are really applied on AVI system in actual steel manufacturing line, and those will be more credible to flat steel manufacturers, as all the results of detection accuracy based on raw images should be evaluated from all the detected defects and actual defects (not on database but on the real-world steel surface), while the actual defects need professional defect inspectors to find out one by one from the historical flat steel products, which are extremely labor-intensive and time-consuming. This is why this kind of studies (see [5]) is quite rare at present. Driven by developments of emerging machine learning and improvements of hardware computing power, algorithmic research will develop toward the urgent needs of engineering applications, and more high-quality achievements can be expected to open in the near future.

This article has summarized the research efforts made over the past two decades about the automated visual defect detection of flat steel surface in industrial manufacturing, where the largest volume of published reports in this literature belongs to the last five years. The research trend has gradually shifted from the previous theoretical study to on-site application. Representative works from statistical, spectral, model-based, and machine learning aspects are listed for readers to have a general overview of the state of the arts. Existing challenges to surface defect detection and some potential proposals are investigated from a systematic perspective as follows.

1) How to make better balance of detection accuracy and computing efficiency is still relatively open to the automated computer-vision-based surface defect detection. However, for the real-world industrial manufacturing of flat steels, detection stability especially robustness to environmental variations is on the very top list.
2) Real-time operation of high-resolution AVI system is expecting fast defect detection. As for algorithm itself, fusing features extracted by multiple descriptors to support final detection decision can yield better results than those produced by a single descriptor in the most cases. Intrinsic priors of the production line are suggested to assist the defect detection. Online surface defect detection prefers lightweight arithmetic methods to complex learning networks, as our problem is an unsupervised and real-time detection task in essence, while machine learning or deep network is the preeminent alternative for complex multiclass classification problem with rich data sets (i.e., defect classification). As the defect detection task can be treated as a biclassification problem, it is not surprising that the machine learning trend is gradually sinking to the discussed defect detection topic. With respect to its resident hardware, the concept of edge computing could be employed for terminal accelerating, that is, ASICs, such as FPGAs, are encouraged to be placed at the front end of image acquisition where preprocessing on raw data can be finished in real-time so as to prevent redundant information being spread to the subsequent transmission and postprocessing.
3) As the prelude of defect detection, noise smoothing and edge enhancing are suggested to be arranged as closer as possible to the imaging sensors; incredibly, the most effective denoising method for AVI system is to make the images as clean as possible by some feasible engineering measures. For example, equipping high-pressure air-gun removing surface water droplets is far more effective than to develop advanced water removal algorithms to eliminate false alarm triggered by pseudodefect. Moreover, adaptive and closed-loop controlling is strongly recommended for the illumination subsystem.
4) It is not prudent to compare detection performance of different techniques as different experiments select different testing methods with different evaluation criteria on distinct data sets. More steel surface defect databases, especially raw images from real-world industrial production line, are urgently expected for enriching diversified and cumulative future research ecology, which will be sure to benefit to explore for a feasible and comparable standard of performance evaluation for distinct defect detection methodologies.
5) We have tried to include as many as possible up-to-date references following the emerging AVI techniques, and it is impossible to comprise all the existing publi-

cations due to space limitations. In addition, the second survey article focusing on surface defect classification techniques about flat steels is under way.

REFERENCES

[1] S. Ghorai, A. Mukherjee, M. Gangadaran, and P. K. Dutta, "Automatic defect detection on hot-rolled flat steel products," *IEEE Trans. Instrum. Meas.*, vol. 62, no. 3, pp. 612–621, Mar. 2013.

[2] K. Song and Y. Yan, "A noise robust method based on completed local binary patterns for hot-rolled steel strip surface defects," *Appl. Surf. Sci.*, vol. 285, pp. 858–864, Nov. 2013.

[3] Q. Luo, Y. Sun, P. Li, O. Simpson, L. Tian, and Y. He, "Generalized completed local binary patterns for time-efficient steel surface defect classification," *IEEE Trans. Instrum. Meas.*, vol. 68, no. 3, pp. 667–679, Mar. 2019.

[4] H. Di, X. Ke, Z. Peng, and Z. Dongdong, "Surface defect classification of steels with a new semi-supervised learning method," *Opt. Lasers Eng.*, vol. 117, pp. 40–48, Jun. 2019.

[5] Q. Luo and Y. He, "A cost-effective and automatic surface defect inspection system for hot-rolled flat steel," *Robot. Comput.-Integr. Manuf.*, vol. 38, pp. 16–30, Apr. 2016.

[6] R. Usamentiaga, D. F. Garcia, J. Molleda, F. G. Bulnes, and G. B. Brana, "Vibrations in steel strips: Effects on flatness measurement and filtering," *IEEE Trans. Ind. Appl.*, vol. 50, no. 5, pp. 3103–3112, Sep. 2014.

[7] G. Wu, H. Zhang, X. Sun, J. Xu, and K. Xu, "A bran-new feature extraction method and its application to surface defect recognition of hot rolled strips," in *Proc. IEEE Int. Conf. Autom. Logistics*, Jinan, China, Aug. 2007, pp. 2069–2074.

[8] A. Kumar, "Computer-vision-based fabric defect detection: A survey," *IEEE Trans. Ind. Electron.*, vol. 55, no. 1, pp. 348–363, Jan. 2008.

[9] N. Neogi, D. K. Mohanta, and P. K. Dutta, "Review of vision-based steel surface inspection systems," *EURASIP J. Image Video Process.*, vol. 2014, no. 1, p. 50, Nov. 2014.

[10] C. A. Mack, "Fifty years of Moore's law," *IEEE Trans. Semicond. Manuf.*, vol. 24, no. 2, pp. 202–207, May 2011.

[11] R. T. Chin and C. A. Harlow, "Automated visual inspection: A survey," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. TPAMI-4, no. 6, pp. 557–573, Dec. 1982.

[12] T. S. Newman and A. K. Jain, "A survey of automated visual inspection," *Comput. Vis. Image Understand.*, vol. 61, no. 2, pp. 231–262, 1995.

[13] X. Xie, "A review of recent advances in surface defect detection using texture analysis techniques," *Electron. Lett. Comput. Vis. Image Anal.*, vol. 7, no. 3, pp. 1–22, Apr. 2008.

[14] S.-H. Huang and Y.-C. Pan, "Automated visual inspection in the semiconductor industry: A survey," *Comput. Ind.*, vol. 66, pp. 1–10, Jan. 2015.

[15] W.-B. Li, C.-H. Lu, and J.-C. Zhang, "A local annular contrast based real-time inspection algorithm for steel bar surface defects," *Appl. Surf. Sci.*, vol. 258, no. 16, pp. 6080–6086, Jun. 2012.

[16] F. Timm and E. Barth, "Non-parametric texture defect detection using Weibull features," *Proc. SPIE*, vol. 7877, Feb. 2011, Art. no. 78770J.

[17] H. Wang, J. Zhang, Y. Tian, H. Chen, H. Sun, and K. Liu, "A simple guidance template-based defect detection method for strip steel surfaces," *IEEE Trans. Ind. Informat.*, vol. 15, no. 5, pp. 2798–2809, May 2019.

[18] S. Youkachen, M. Ruchanurucks, T. Phatrapomnant, and H. Kaneko, "Defect segmentation of hot-rolled steel strip surface by using convolutional auto–encoder and conventional image processing," in *Proc. 10th Int. Conf. Inf. Commun. Technol. Embedded Syst. (IC-ICTES)*, Bangkok, Thailand, Mar. 2019, pp. 1–5.

[19] G. Wu, H. Kwak, S. Jang, K. Xu, and J. Xu, "Design of online surface inspection system of hot rolled strips," in *Proc. IEEE Int. Conf. Autom. Logistics*, Qingdao, China, Sep. 2008, pp. 2291–2295.

[20] M. Sharifzadeh, S. Alirezaee, R. Amirfattahi, and S. Sadri, "Detection of steel defect using the image processing algorithms," in *Proc. IEEE Int. Multitopic Conf.* Karachi, Pakistan: Bahria Univ., Feb. 2009, pp. 125–127.

[21] D. Djukic and S. Spuzic, "Statistical discriminator of surface defects on hot rolled steel," in *Proc. Image Vis. Comput.*, Dec. 2007, pp. 158–163.

[22] G. K. Nand, Noopur, and N. Neogi, "Defect detection of steel surface using entropy segmentation," in *Proc. Annu. IEEE India Conf. (INDICON),* Pune, India, Dec. 2014, pp. 1–6.

[23] N. Neogi, D. K. Mohanta, and P. K. Dutta, "Defect detection of steel surfaces with global adaptive percentile thresholding of gradient image," *J. Inst. Eng. (India), B*, vol. 98, no. 6, pp. 557–565, Dec. 2017.

[24] F. G. Bulnes, R. Usamentiaga, D. F. García, and J. Molleda, "Vision-based sensor for early detection of periodical defects in Web materials," *Sensors*, vol. 12, no. 8, pp. 10788–10809, Aug. 2012.

[25] Y. J. Zhao, Y. H. Yan, and K. C. Song, "Vision-based automatic detection of steel surface defects in the cold rolling process: Considering the influence of industrial liquids and surface textures," *Int. J. Adv. Manuf. Technol.*, vol. 90, nos. 5–8, pp. 1665–1678, May 2017.

[26] J. Wang, Q. Li, J. Gan, H. Yu, and X. Yang, "Surface defect detection via entity sparsity pursuit with intrinsic priors," *IEEE Trans. Ind. Informat.*, to be published.

[27] A. Borselli, V. Colla, M. Vannucci, and M. Veroli, "A fuzzy inference system applied to defect detection in flat steel production," in *Proc. Int. Conf. Fuzzy Syst.*, Barcelona, Spain, Jul. 2010, pp. 1–6.

[28] T. Shi, J.-Y. Kong, X.-D. Wang, Z. Liu, and G. Zheng, "Improved Sobel algorithm for defect detection of rail surfaces with enhanced efficiency and accuracy," *J. Central South Univ.*, vol. 23, no. 11, pp. 2867–2875, Nov. 2016.

[29] B. Tang, J.-Y. Kong, X.-D. Wang, and L. Chen, "Surface inspection system of steel strip based on machine vision," in *Proc. First Int. Workshop Database Technol. Appl.*, Wuhan, Hubei, China, Apr. 2009, pp. 359–362.

[30] A. L. Zhiznyakov, D. G. Privezentsev, and A. A. Zakharov, "Using fractal features of digital images for the detection of surface defects," *Pattern Recognit. Image Anal.*, vol. 25, no. 1, pp. 122–131, Jan. 2015.

[31] M. Yazdchi, M. Yazdi, and A. G. Mahyari, "Steel surface defect detection using texture segmentation based on multifractal dimension," in *Proc. Int. Conf. Digit. Image Process.*, Bangkok, Thailand, Mar. 2009, pp. 346–350.

[32] S.-S. Yang, Y.-H. He, Z.-L. Wang, and W.-S. Zhao, "A method of steel strip image segmentation based on local gray information," in *Proc. IEEE Int. Conf. Ind. Technol.*, Chengdu, China, Apr. 2008, pp. 1–4.

[33] J. Choi and C. Kim, "Unsupervised detection of surface defects: A two-step approach," in *Proc. 19th IEEE Int. Conf. Image Process.*, Orlando, FL, USA, Sep. 2012, pp. 1037–1040.

[34] Y. Ma, Q. Li, Y. Zhou, F. He, and S. Xi, "A surface defects inspection method based on multidirectional gray-level fluctuation," *Int. J. Adv. Robotic Syst.*, vol. 14, no. 3, May 2017, Art. no. 1729881417703114.

[35] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural features for image classification," *IEEE Trans. Syst., Man, Cybern.*, vol. SMC-3, no. 6, pp. 610–621, Nov. 1973.

[36] J. Zhou *et al.*, "The effects of GLCM parameters on LAI estimation using texture values from quickbird satellite imagery," *Sci. Rep.*, vol. 7, Aug. 2017, Art. no. 7366.

[37] Z. Xing and H. Jia, "Multilevel color image segmentation based on GLCM and improved salp swarm algorithm," *IEEE Access*, vol. 7, pp. 37672–37690, 2019.

[38] R. B. Vallabhaneni and V. Rajesh, "Brain tumour detection using mean shift clustering and GLCM features with edge adaptive total variation denoising technique," *Alexandria Eng. J.*, vol. 57, no. 4, pp. 2387–2392, Dec. 2018.

[39] Y. Wang, H. Xia, X. Yuan, L. Li, and B. Sun, "Distributed defect recognition on steel surfaces using an improved random forest algorithm with optimal multi-feature-set fusion," *Multimed. Tools Appl.*, vol. 77, no. 13, pp. 16741–16770, Jul. 2018.

[40] D.-M. Tsai, M.-C. Chen, W.-C. Li, and W.-Y. Chiu, "A fast regularity measure for surface defect detection," *Mach. Vis. Appl.*, vol. 23, no. 5, pp. 869–886, Sep. 2012.

[41] M. Chu and R. Gong, "Invariant feature extraction method based on smoothed local binary pattern for strip steel surface defect," *ISIJ Int.*, vol. 55, no. 9, pp. 1956–1962, 2015.

[42] T. Ojala, M. Pietikäinen, and D. Harwood, "A comparative study of texture measures with classification based on featured distributions," *Pattern Recognit.*, vol. 29, no. 1, pp. 51–59, Jan. 1996.

[43] M. Chu, R. Gong, S. Gao, and J. Zhao, "Steel surface defects recognition based on multi-type statistical features and enhanced twin support vector machine," *Chemometrics Intell. Lab. Syst.*, vol. 171, pp. 140–150, Dec. 2017.

[44] Y. Liu, K. Xu, and D. Wang, "Online surface defect identification of cold rolled strips based on local binary pattern and extreme learning machine," *Metals*, vol. 8, no. 3, p. 197, Mar. 2018.

[45] J. Zhao, Y. Peng, and Y. Yan, "Steel surface defect classification based on discriminant manifold regularized local descriptor," *IEEE Access*, vol. 6, pp. 71719–71731, 2018.

[46] Q. Luo *et al.*, "Surface defect classification for hot–rolled steel strips by selectively dominant local binary patterns," *IEEE Access*, vol. 7, pp. 23488–23499, 2019.

[47] F. Dupont, C. Odet, and M. Cartont, "Optimization of the recognition of defects in flat steel products with the cost matrices theory," *NDT&E Int.*, vol. 30, no. 1, pp. 3–10, Feb. 1997.

[48] M. González-Hidalgo, S. Massanet, A. Mir, and D. Ruiz-Aguilera, "Improving salt and pepper noise removal using a fuzzy mathematical morphology-based filter," *Appl. Soft Comput.*, vol. 63, pp. 167–180, Feb. 2018.

[49] H. Zheng, L. Kong, and S. Nahavandi, "Automatic inspection of metallic surface defects using genetic algorithms," *J. Mater. Process. Technol.*, vols. 125–126, pp. 427–433, Sep. 2002.

[50] D.-C. Choi, Y.-J. Jeon, J. P. Yun, and S. W. Kim, "Pinhole detection in steel slab images using Gabor filter and morphological features," *Appl. Opt.*, vol. 50, no. 26, pp. 5122–5129, Sep. 2011.

[51] X. Li, S. K. Tso, X.-P. Guan, and Q. Huang, "Improving automatic detection of defects in castings by applying wavelet technique," *IEEE Trans. Ind. Electron.*, vol. 53, no. 6, pp. 1927–1934, Dec. 2006.

[52] M. Liu, Y. Liu, H. Hu, and L. Nie, "Genetic algorithm and mathematical morphology based binarization method for strip steel defect image with non-uniform illumination," *J. Vis. Commun. Image Represent.*, vol. 37, pp. 70–77, May 2016.

[53] K.-C. Song, S.-P. Hu, Y.-H. Yan, and J. Li, "Surface defect detection method using saliency linear scanning morphology for silicon steel strip under oil pollution interference," *ISIJ Int.*, vol. 54, no. 11, pp. 2598–2607, 2014.

[54] D. Chetverikov and A. Hanbury, "Finding defects in texture using regularity and local orientation," *Pattern Recognit.*, vol. 35, no. 10, pp. 2165–2180, Oct. 2002.

[55] B. R. Suresh, R. A. Fundakowski, T. S. Levitt, and J. E. Overland, "A real-time automated visual inspection system for hot steel slabs," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-5, no. 6, pp. 563–572, Nov. 1983.

[56] Y.-H. Ai and K. Xu, "Surface detection of continuous casting slabs based on curvelet transform and Kernel locality preserving projections," *J. Iron Steel Res. Int.*, vol. 20, no. 5, pp. 80–86, May 2013.

[57] D. Aiger and H. Talbot, "The phase only transform for unsupervised surface defect detection," in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, San Francisco, CA, USA, Jun. 2010, pp. 295–302.

[58] S. Xie, S. Shan, X. Chen, and J. Chen, "Fusing local patterns of Gabor magnitude and phase for face recognition," *IEEE Trans. Image Process.*, vol. 19, no. 5, pp. 1349–1361, May 2010.

[59] J. Kim, S. Um, and D. Min, "Fast 2D complex Gabor filter with Kernel decomposition," *IEEE Trans. Image Process.*, vol. 27, no. 4, pp. 1713–1722, Apr. 2018.

[60] A. Bodnarova, M. Bennamoun, and S. Latham, "Optimal Gabor filters for textile flaw detection," *Pattern Recognit.*, vol. 35, no. 12, pp. 2973–2991, Dec. 2002.

[61] Z. Ni, H. Zeng, L. Ma, J. Hou, J. Chen, and K.-K. Ma, "A Gabor feature–based quality assessment model for the screen content images," *IEEE Trans. Image Process.*, vol. 27, no. 9, pp. 4516–4528, Sep. 2018.

[62] Y.-J. Jeon, D.-C. Choi, J. Yun, and S. Kim, "Detection of periodic defects using dual-light switching lighting method on the surface of thick plates," *ISIJ Int.*, vol. 55, no. 9, pp. 1942–1949, 2015.

[63] J. P. Yun, D. Kim, K. Kim, S. J. Lee, C. H. Park, and S. W. Kim, "Vision-based surface defect inspection for thick steel plates," *Opt. Eng.*, vol. 56, no. 5, May 2017, Art. no. 053108.

[64] D.-C. Choi, Y.-J. Jeon, S. H. Kim, S. Moon, J. P. Yun, and S. W. Kim, "Detection of pinholes in steel slabs using Gabor filter combination and morphological features," *ISIJ Int.*, vol. 57, no. 6, pp. 1045–1053, 2017.

[65] R. Medina *et al.*, "Automated visual classification of frequent defects in flat steel coils," *Int. J. Adv. Manuf. Technol.*, vol. 57, nos. 9–12, pp. 1087–1097, Dec. 2011.

[66] A. Tolba, "Fast defect detection in homogeneous flat surface products," *Expert Syst. Appl.*, vol. 38, no. 10, pp. 12339–12347, Sep. 2011.

[67] A. G. Zuñiga, J. B. Florindo, and O. M. Bruno, "Gabor wavelets combined with volumetric fractal dimension applied to texture analysis," *Pattern Recognit. Lett.*, vol. 36, pp. 135–143, Jan. 2014.

[68] T. Randen and J. Husoy, "Texture segmentation using filters with optimized energy separation," *IEEE Trans. Image Process.*, vol. 8, no. 4, pp. 571–582, Apr. 1999.

[69] A. Kumar, "Automated defect defection in textured materials," Ph.D. dissertation, Dept. Elect. Electron. Eng., Univ. Hong Kong, Hong Kong, May 2001.

[70] A. Kumar and G. Pang, "Defect detection in textured materials using optimized filters," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 32, no. 5, pp. 553–570, Oct. 2002.

[71] A. Kumar, "Inspection of surface defects using optimal FIR filters," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, Hong Kong, Dec. 2003, pp. 241–244.

[72] Y.-J. Jeon, D.-C. Choi, S. J. Lee, J. P. Yun, and S. W. Kim, "Steel-surface defect detection using a switching-lighting scheme," *Appl. Opt.*, vol. 55, no. 1, pp. 47–57, Jan. 2016.

[73] W. Liu and Y. Yan, "Automated surface defect detection for cold-rolled steel strip based on wavelet anisotropic diffusion method," *Int. J. Ind. Syst. Eng.*, vol. 17, no. 2, p. 224, 2014.

[74] X.-Y. Wu, K. Xu, and J.-W. Xu, "Application of undecimated wavelet transform to surface defect detection of hot rolled steel plates," in *Proc. Congr. Image Signal Process.*, Sanya, Hainan, China, May 2008, pp. 528–532.

[75] K. Song, S. Hu, and Y. Yan, "Automatic recognition of surface defects on hot-rolled steel strip using scattering convolution network," *J. Comput. Inf. Syst.*, vol. 10, no. 7, pp. 3049–3055, Apr. 2014.

[76] E. Le Pennec and S. Mallat, "Sparse geometric image representations with bandelets," *IEEE Trans. Image Process.*, vol. 14, no. 4, pp. 423–438, Apr. 2005.

[77] J. Krommweh, "Tetrolet transform: A new adaptive Haar wavelet algorithm for sparse image representation," *J. Vis. Commun. Image Represent.*, vol. 21, no. 4, pp. 364–374, May 2010.

[78] X. Zhang, Y. H. Yan, W. H. Chen, and J. J. Chen, "Image fusion method for strip steel surface detect based on bandelet–PCNN," *Adv. Mater. Res.*, vols. 546–547, pp. 806–810, Jul. 2012.

[79] K. Xu, S. Liu, and Y. Ai, "Application of shearlet transform to classification of surface defects for metals," *Image Vis. Comput.*, vol. 35, pp. 23–30, Mar. 2015.

[80] K. Xu, Y. Xu, P. Zhou, and L. Wang, "Application of RNAM let to surface defect identification of steels," *Opt. Lasers Eng.*, vol. 105, pp. 110–117, Jun. 2018.

[81] E. J. Candes and D. L. Donoho, "Ridgelets: Theory and applications," in *Proc. ICASE/LARC*, 1998.

[82] E. Candès, L. Demanet, D. Donoho, and L. Ying, "Fast discrete curvelet transforms," *Multiscale Model. Simul.*, vol. 5, no. 3, pp. 861–899, Jan. 2006.

[83] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, 3rd ed. 2007.

[84] X. Si, J. Feng, J. Zhou, and Y. Luo, "Detection and rectification of distorted fingerprints," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 37, no. 3, pp. 555–568, Mar. 2015.

[85] S. Gu, J. Feng, J. Lu, and J. Zhou, "Efficient rectification of distorted fingerprints," *IEEE Trans. Inf. Forensics Security*, vol. 13, no. 1, pp. 156–169, Jan. 2018.

[86] T. D. Duan, D. A. Duc, and T. Le Hong Du, "Combining Hough transform and contour algorithm for detecting vehicles' license-plates," in *Proc. Int. Symp. Intell. Multimedia, Video Speech Process.*, Hong Kong, Oct. 2004, pp. 747–750.

[87] G. R. Cross and A. K. Jain, "Markov random field texture models," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-5, no. 1, pp. 25–39, Jan. 1983.

[88] F. Gayubo, J. González, E. De La Fuente, F. Miguel, and J. Perán, "On-line machine vision system for detect split defects in sheet-metal forming processes," in *Proc. 18th Int. Conf. Pattern Recognit. (ICPR)*, Hong Kong, Aug. 2006, pp. 723–726.

[89] K. Xu, "Application of hidden Markov tree model to on-line detection of surface defects for steel strips," *J. Mech. Eng.*, vol. 49, no. 22, pp. 34–40, Nov. 2013.

[90] I. Ben Ayed, N. Hennane, and A. Mitiche, "Unsupervised variational image segmentation/classification using a Weibull observation model," *IEEE Trans. Image Process.*, vol. 15, no. 11, pp. 3431–3439, Nov. 2006.

[91] K. Liu, H. Wang, H. Chen, E. Qu, Y. Tian, and H. Sun, "Steel surface defect detection using a new Haar–Weibull-variance model in unsupervised manner," *IEEE Trans. Instrum. Meas.*, vol. 66, no. 10, pp. 2585–2596, Oct. 2017.

[92] B. Wu and Y. Yang, "Local- and global-statistics-based active contour model for image segmentation," *Math. Problems Eng.*, vol. 2012, pp. 1–16, Apr. 2012.

[93] L. Wang, Y. Chang, H. Wang, Z. Wu, J. Pu, and X. Yang, "An active contour model based on local fitted images for image segmentation," *Inf. Sci.*, vols. 418–419, pp. 61–73, Dec. 2017.

[94] K. Song and Y. Yan, "Micro surface defect detection method for silicon steel strip based on saliency convex active contour model," *Math. Problems Eng.*, vol. 2013, pp. 1–13, Nov. 2013.

[95] J. Yang *et al.*, "Development of an optical defect inspection algorithm based on an active contour model for large steel roller surfaces," *Appl. Opt.*, vol. 57, no. 10, p. 2490, Apr. 2018.

[96] S. Susan and M. Sharma, "Automatic texture defect detection using Gaussian mixture entropy modeling," *Neurocomputing*, vol. 239, pp. 232–237, May 2017.

[97] H. Yan, K. Paynabar, and J. Shi, "Anomaly detection in images with smooth background via smooth-sparse decomposition," *Technometrics*, vol. 59, no. 1, pp. 102–114, 2017.

[98] Q. Huangpeng, H. Zhang, X. Zeng, and W. Huang, "Automatic visual defect detection using texture prior and low-rank representation," *IEEE Access*, vol. 6, pp. 37965–37976, 2018.

[99] S. Zhou, S. Wu, H. Liu, Y. Lu, and N. Hu, "Double low–rank and sparse decomposition for surface defect segmentation of steel sheet," *Appl. Sci.*, vol. 8, no. 9, pp. 1628–1643, Sep. 2018.

[100] D.-C. Choi, Y.-J. Jeon, S. J. Lee, J. P. Yun, and S. W. Kim, "Algorithm for detecting seam cracks in steel plates using a Gabor filter combination method," *Appl. Opt.*, vol. 53, no. 22, pp. 4865–4872, Aug. 2014.

[101] M. W. Ashour, F. Khalid, A. Abdul Halin, L. N. Abdullah, and S. H. Darwish, "Surface defects classification of hot-rolled steel strips using multi-directional shearlet features," *Arabian J. Sci. Eng.*, vol. 44, no. 4, pp. 2925–2932, Apr. 2019.

[102] G.-W. Kang and H.-B. Liu, "Surface defects inspection of cold rolled strips based on neural network," in *Proc. Int. Conf. Mach. Learn. Cybern.*, Guangzhou, China, Aug. 2005, pp. 5034–5037.

[103] D. Weimer, B. Scholz-Reiter, and M. Shpitalni, "Design of deep convolutional neural network architectures for automated feature extraction in industrial inspection," *CIRP Ann.-Manuf. Technol.*, vol. 65, no. 1, pp. 417–420, 2016.

[104] J.-K. Park, B.-K. Kwon, J.-H. Park, and D.-J. Kang, "Machine learning-based imaging system for surface defect inspection," *Int. J. Precis. Eng. Manuf.-Green Technol.*, vol. 3, no. 3, pp. 303–310, Jul. 2016.

[105] Y.-J. Cha, W. Choi, and O. Büyüköztürk, "Deep learning-based crack damage detection using convolutional neural networks," *Comput.-Aided Civil Infrastruct. Eng.*, vol. 32, no. 5, pp. 361–378, May 2017.

[106] D. He, K. Xu, and P. Zhou, "Defect detection of hot rolled steels with a new object detection framework called classification priority network," *Comput. Ind. Eng.*, vol. 128, pp. 290–297, Feb. 2019.

[107] Y. Liu, K. Xu, and J. Xu, "Periodic surface defect detection in steel plates based on deep learning," *Appl. Sci.*, vol. 9, no. 15, p. 3127, Aug. 2019.

[108] L. Song, W. Lin, Y.-G. Yang, X. Zhu, Q. Guo, and J. Xi, "Weak micro-scratch detection based on deep convolutional neural network," *IEEE Access*, vol. 7, pp. 27547–27554, 2019.

[109] Y.-J. Cha, W. Choi, G. Suh, S. Mahmoudkhani, and O. Büyüköztürk, "Autonomous structural visual inspection using region-based deep learning for detecting multiple damage types," *Comput.-Aided Civil Infrastruct. Eng.*, vol. 33, no. 9, pp. 731–747, Sep. 2018.

[110] J. Li, Z. Su, J. Geng, and Y. Yin, "Real-time detection of steel strip surface defects based on improved YOLO detection network," in *Proc. IFAC Works*. Shanghai, China: MMM, 2018, pp. 76–81.

[111] A. Radford, L. Metz, and S. Chintala, "Unsupervised representation learning with deep convolutional generative adversarial networks," in *Proc. Int. Conf. Learn. Represent.*, San Juan, Puerto Rico, May 2016, pp. 1–16.

[112] T. Schlegl, P. Seeboeck, S. M. Waldstein, U. Schmidt-Erfurth, and G. Langs, "Unsupervised anomaly detection with generative adversarial networks to guide marker discovery," in *Information Processing in Medical Imaging*, Boone, NC, USA: Appalachian State Univ., Jun. 2017, pp. 146–157.

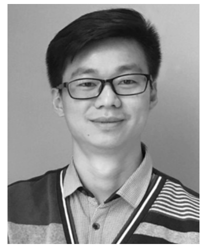
[113] Z. Zhao, B. Li, R. Dong, and P. Zhao, "A surface defect detection method based on positive samples," in *PRICAI: Trends in Artificial Intelligence* (Lecture Notes in Computer Science). Nanjing, China, Aug. 2018, pp. 473–481.

[114] S. Mei, H. Yang, and Z. Yin, "An unsupervised-learning-based approach for automated defect inspection on textured surfaces," *IEEE Trans. Instrum. Meas.*, vol. 67, no. 6, pp. 1266–1277, Jun. 2018.

[115] R. Ren, T. Hung, and K. C. Tan, "A generic deep-learning-based approach for automated surface inspection," *IEEE Trans. Cybern.*, vol. 48, no. 3, pp. 929–940, Mar. 2018.

[116] X. Tao, D. Zhang, W. Ma, X. Liu, and D. Xu, "Automatic metallic surface defect detection and recognition with convolutional neural networks," *Appl. Sci.*, vol. 8, no. 9, p. 1575, Sep. 2018.

[117] F. Zhou, G. Liu, F. Xu, and H. Deng, "A generic automated surface defect detection based on a bilinear model," *Appl. Sci.*, vol. 9, no. 15, p. 3159, Aug. 2019.



Qiwu Luo (Member, IEEE) received the B.S. degree in communication engineering from the National University of Defense Technology, Changsha, China, in 2008, and the M.Sc. degree in electronic science and technology and the Ph.D. degree in electrical engineering from Hunan University, Changsha, in 2011 and 2016, respectively.

He was a Senior Engineer of instrumentation with WASION Group Ltd. Company, Changsha, and the Deputy Technical Director with Hunan RAMON Technology Company, Ltd., Changsha. In 2016, he joined the School of Electrical Engineering and Automation, Hefei University of Technology, Hefei, China, where he also completed his post-doctoral research on automatic optic inspection (AOI). He is currently an Associate Professor with the School of Automation, Central South University, Changsha. His current research interests include computer vision, industrial AOI, machine learning, parallel hardware architecture design, and reconfigurable computing.

Xiaoxin Fang received the B.S. degree in electrical engineering and automation from the Jiangsu University of Science and Technology, Zhenjiang, China, in 2018. He is currently pursuing the M.Sc. degree with the School of Electrical Engineering and Automation, Hefei University of Technology, Hefei, China, under the guidance of Dr. Q. Luo.

His current research interests include texture analysis and image classification.

Li Liu received the B.Sc. degree in communication engineering, the M.Sc. degree in photogrammetry and remote sensing, and the Ph.D. degree in information and communication engineering from the National University of Defense Technology (NUDT), Changsha, China, in 2003, 2005, and 2012, respectively.

During her Ph.D. study, she spent more than two years as a Visiting Student at the University of Waterloo, Waterloo, ON, Canada, from 2008 to 2010. In 2012, she joined the faculty at NUDT, where she was an Associate Professor with the College of System Engineering. From 2015 to 2016, she spent ten months visiting the Multimedia Laboratory at The Chinese University of Hong Kong, Hong Kong. From December 2016 to September 2018, she worked as a Senior Researcher at the Machine Vision Group, University of Oulu, Oulu, Finland. She is currently with the University of Oulu. Her articles have currently over 1800 citations in Google Scholar. Her current research interests include facial behavior analysis, texture analysis, image classification, object detection, and recognition.

Dr. Liu was the Co-Chair of the International Workshops at the Asian Conference on Computer Vision (ACCV) 2014, the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2016, the IEEE International Conference on Computer Vision (ICCV) 2017, the European Conference on Computer Vision (ECCV) 2018, and CVPR 2019. She is organizing a tutorial on Textures, Objects and Scenes at CVPR 2019. She was a Guest Editor of special issues for the IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE and the *International Journal of Computer Vision*. She also serves as an Associate Editor for *The Visual Computer* journal.

Chunhua Yang (Member, IEEE) received the M.S. degree in automatic control engineering and the Ph.D. degree in control science and engineering from Central South University, Changsha, China, in 1988 and 2002, respectively.

From 1999 to 2001, she was a Visiting Professor with the University of Leuven, Leuven, Belgium. Since 1999, she has been a Full Professor with the School of Information Science and Engineering, Central South University. From 2009 to 2010, she was a Senior Visiting Scholar with the University of Western Ontario, London, ON, Canada. She is currently the HoD of the School of Automation, Central South University. Her current research interests include modeling and optimal control of complex industrial processes, and intelligent control systems.

Yichuang Sun (Senior Member, IEEE) received the B.Sc. and M.Sc. degrees in communications and electronics engineering from Dalian Maritime University, Dalian, China, in 1982 and 1985, respectively, and the Ph.D. degree in communications and electronics engineering from the University of York, York, U.K., in 1996.

He is currently a Professor of communications and electronics and the Head of the Communications and Intelligent Systems Research Group and the Electronic, Communication and Electrical Engineering Division, School of Engineering and Computer Science, University of Hertfordshire, Hatfield, U.K. He has published over 330 articles and contributed ten chapters in edited books. He has also published four text and research books: *Continuous-Time Active Filter Design* (USA: CRC Press, 1999), *Design of High Frequency Integrated Analog Filters* (U.K., IEE Press, 2002), *Wireless Communication Circuits and Systems* (IET Press, 2004), and *Test and Diagnosis of Analog, Mixed-signal and RF Integrated Circuits: The Systems on Chip Approach* (IET Press, 2008). His research interests are in the areas of wireless and mobile communications, RF and analog circuits, microelectronic devices and systems, and machine learning and deep learning.

Dr. Sun was a Series Editor of IEE Circuits, Devices and Systems Book Series from 2003 to 2008. He has been an Associate Editor of the IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS—I: REGULAR ARTICLES from 2010 to 2011, 2016 to 2017, and 2018 to 2019. He is also an Editor of the *ETRI Journal*, the *Journal of Semiconductors*, and the *Journal of Sensor and Actuator Networks*. He was a Guest Editor of eight IEEE and IEE/IET journal special issues: High-frequency Integrated Analog Filters in the *IEE Proceedings—Circuits, Devices and Systems* in 2000, RF Circuits and Systems for Wireless Communications in *IEE Proceedings—Circuits, Devices and Systems* in 2002, Analog and Mixed-Signal Test for Systems on Chip in the *IEE Proceedings—Circuits, Devices and Systems* in 2004, MIMO Wireless and Mobile Communications in *IEE Proceedings—Communications* in 2006, Advanced Signal Processing for Wireless and Mobile Communications in the *IET Signal Processing* in 2009, Cooperative Wireless and Mobile Communications in the *IET Communications* in 2013, Software-Defined Radio Transceivers and Circuits for 5G Wireless Communications in the IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS—II in 2016, and the 2016 IEEE International Symposium on Circuits and Systems in the IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS—I in 2016. He has also been widely involved in various IEEE technical committee and international conference activities.