Received: 28 January 2022 | Revised: 27 August 2022 | Accepted: 19 September 2022

DOI: 10.1049/ipr2.12647

IET Image Processing

The Institution of Engineering and Technology WILEY

REVIEW

Review of surface defect detection of steel products based on machine vision

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Funding information
National Natural Science Foundation of China, Grant/Award Number: 51874217

Abstract
Steel plays an important role in industry, and the surface defect detection for steel products based on machine vision has been widely used during the last two decades. This paper attempts to review state-of-art of vision-based surface defect inspection technology of steel products by investigating about 170 publications. This review covers the overall aspects of vision-based surface defect inspection for steel products including hardware system, automated vision-based inspection method, existing problems and latest development. The types of steel product surface defects composition of visual inspection system are briefly described, and image acquisition system is introduced as well. The image processing algorithms for surface defect detection of steel products are reviewed, including image pre-processing, region of interest (ROI) detection, image segmentation for ROI, feature extraction and selection and defect classification. The important problems such as small sample and real time of steel surface defect detection are discussed. Finally, the challenge and development trend of steel surface defect detection are prospected.

1 | INTRODUCTION

Steel plays an important role for automobile, shipbuilding, machinery manufacturing, aerospace and other industries. There are different types of surface defects in steel products manufacturing process due to various reasons such as raw materials, equipment and processing technology. These defects will have adverse effects on the appearance, corrosion resistance and fatigue strength of the product.

In the 1980s, researchers began to use machine vision method to inspect steel surface defects. In the 1990s, Cognex, Parsytec, EES, ABB and some other companies applied machine vision methods to online detect steel surface defects. Nowadays, vision-based automatic surface inspection system (ASIS) has been more and more studied and applied.

A typical visual surface detection system includes image acquisition unit, image processing unit, data management and human–computer interface unit (Figure 1). The image acquisition unit is mainly composed of light source, camera and lens. The image processing unit mainly includes image pre-processing, region of interest (ROI) detection, image segmentation, feature extraction and selection and defects classification.

The flow of traditional target detection algorithm based on machine vision is as follows.

- Image pre-processing: the main purpose is to reduce noise, improve image quality and make it more suitable for machine processing.
- ROI detection: it is used to judge whether there is a suspected surface defect area in the image.
- Image segmentation: detect surface defect region of the image and segment ROI from it.
- Feature extraction: extract the features of the ROI, and reduce the dimension of multi-dimensional features.
- Defect classification: the classifier is used to identify types of defects.

Image pre-processing and ROI detection are processed in real time for each image during online detection; when ROI is detected, the subsequent process is carried out in a just-in-time way.

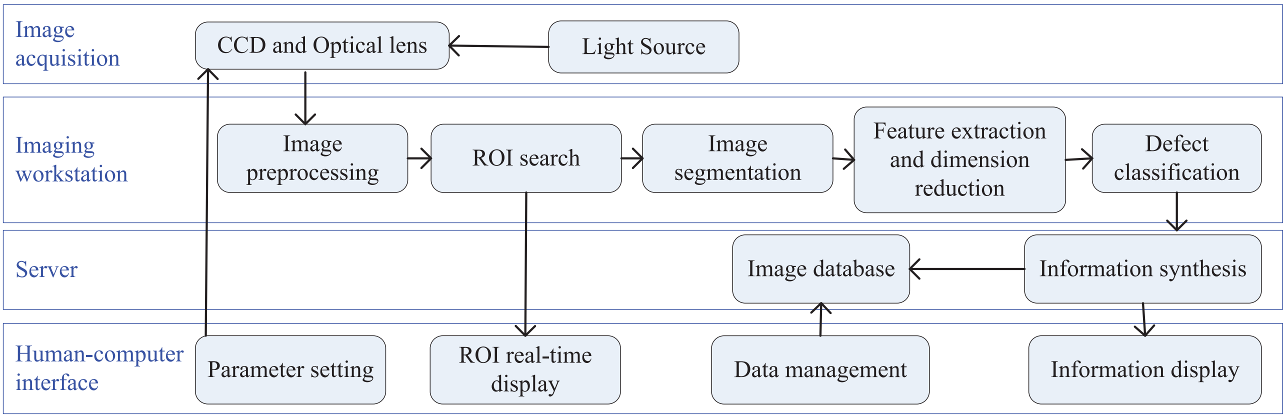

FIGURE 1 Composition of visual inspection system

In recent years, the target detection algorithm based on deep learning (DL) has attracted extensive attention. It usually uses convolutional neural network (CNN) to realize automatic feature extraction, and then uses neural network to realize classification and location. This paper mainly summarizes the traditional image processing algorithms.

In the recent 10 years, some literatures on surface detection based on machine vision have been published. Newman et al. [1] reviewed the common approaches of automatic visual inspection systems and techniques for a wide range of objects reported in the literature from 1988 to 1993. Xie et al. [2] presented the progress of surface inspection using computer vision and image processing technology. However, this paper is mainly based on texture analysis methods, and also for a wide range of objects. Recently, Czimmermann et al. [3] reviewed automated visual-based defect detection approaches with a survey of textural defect detection based on statistical, structural and so on, and reported supervised and non-supervised classifiers and DL method for defects detection. However, the objects discussed here include various materials, such as metals, ceramics and textiles, and are not specific to steel products. In addition, there are some reviews focusing on fabrics, ceramics, PCB and so on.

In the past 10 years, there have been some reviews of automatic surface defect detection for steel products. Li et al. [4] presented review of vision real-time inspection algorithm only for rolling steel surface defects. A comprehensive review of automatic steel surface defect detection and classification systems using vision-based techniques was presented by Neogi [5] in 2014. Both of them do not reflect the latest achievements in recent years. Sun et al. [6] summarized the visual inspection technology of steel products, but there was basically no three-dimensional (3D) inspection of surface defects. Luo et al. [7, 8] reviewed the detection and classification of surface defects of flat steel, respectively, but mainly aimed at flat steel such as continuous casting slab, hot rolled steel strip and cold rolled steel strip, moreover, 3D detection of defects was basically not discussed.

In Section 2, the types of surface defects for steel products are presented. Section 3 and Section 4 review the image acquisition system and the image processing algorithm, respectively. Discussion and summary are explained in Section 5.

2 | TYPES OF SURFACE DEFECTS FOR STEEL PRODUCT

2.1 | Types of steel surface defects

There is no unified standard for the definition and classification of steel surface defects. Even steel produced by the same processing method sometimes has different surface defects. Table 1 lists some typical surface defects of steel.

2.2 | Data sets for defect detection

Data set is the basis of CV task, especially object detection based on DL, which requires a large number of samples. The commonly used data sets in object detection include ImageNet, CCOCO, Pascal VOC and CIFAR. In the field of ASIS, data sets

TABLE 1 Common defect types of steel surface

Steel type	Types of surface defect
Continuous casting	Longitudinal cracks, transverse cracks, crazing, pit, inclusion, pinhole
Hot strip	Scratch, hole, crack, pit, shell, blister, scab, lamination, spill, pore, rolled-in scale, pitting, roll marks, dent, lap
Cold strip	Scratch, hole, crack, pit, blister, crack, scab, shell, lamination, emulsion spot, pitting, oxide scale, temper color, dent, rust, chattering mark, roll mark, black stain, dark line, pimple, patch, inclusion
Rod/bar	Crack, ear, lap, scab, scratch, pitting, lamination, oxidation, decarburization, dark line, crack, scarring, roller printing, scratches, holes, scales, pitting
Pipe	Crack, lap, pit, shell, sand hole, scratch, pitting, scab, seam
Section steel	Lap, scratch, scab, pitting, pit, lamination, blister, crack, seam, ear, shell

of surface defects such as wood, magnetic tile, PCB board and metal are currently opened.

In terms of steel surface defect detection, although many researchers have collected their own steel surface defect images, they do not open their data sets. At present, the most cited data set of steel strip surface defects is NEU-DET [9]. In addition, Amin et al. [10] also opened its steel strip surface defect data set, and rail surface defect data set RSDDs [11] were public by Li et al.

Neu-det data set collects six typical surface defect images of strip steel, namely, rolled in scale (Rs), patches (Pa), cracking (Cr), pitted surface (Ps), inclusion (In) and scratch (Sc). There are 1800 greyscale samples and 300 images in each class. The data set also provides annotation, for defects detection.

The data set of strip steel surface defects provided by Amin has 12,568 training images and 1801 test images, and the image size is 1600×256×1.

The rail surface defect data set RSDDs has type I and type II samples with a resolution of, respectively, 1000×160 and 1250×55 greyscale image.

3 | IMAGE ACQUISITION SYSTEM

3.1 | Camera

Camera is one of the key components of visual inspection system. CCD (charge coupled device) and CMOS (comprehensive metal oxide semiconductor) sensors are two widely used in cameras. CCD has a series of advantages such as wide dynamic range, high sensitivity and resolution, small distortion and volume; CMOS has the characteristics of low cost and power consumption and high degree of integration. The gap between CMOS and CCD tends to narrow gradually.

CCD camera includes line scanning and area scanning according to the arrangement of photosensitive units. Line scan CCD can achieve high scanning frequency and realize continuous detection of moving objects, but the measured object and camera need to move at a relatively uniform speed, and the illumination should be uniform; area scan CCD camera can obtain two-dimensional (2D) image information, but it is difficult to meet the requirements of large field of view and high resolution. Zhao et al. [12] established a multi-source imaging system combined with line array and area array CCD with linear laser transmitter, using fuzzy-rough sets method to detect 3D defects for hot slab surface.

Multiple cameras are required if one camera cannot scan the entire steel surface. When the upper and lower surfaces of the steel plate need to be detected, the same imaging device will be configured on the two sides of the steel plate. Peng et al. [13] used time delayed integration (TDI) CCD for the tinned strip steel surface detection where two 4K pixel cameras are used for both sides, respectively, and the resolution of detected defects reached 0.16 mm × 0.16 mm. Yun et al. [14] placed a total of 22 line scan cameras at both sides of surfaces for steel thick plates to cover the whole width of the plates and used dual switching lights to distinguish uneven defects and colour changes, which repeat on/off operations by synchronizing the lights with the moving speed of plates. Wu et al. [15] equipped with 20 area scan CCD cameras used to capture both sides of images of hot rolled strips simultaneously.

Wire surface defect detection has the following special features compared with flat steel: The wire has a long cylindrical structure, which usually causes the image to be bright in the middle and gradually darken to the boundary; the oxide scale on its surface will change the reflection characteristics and make the image illumination uneven; the production speed of wire rod is fast, up to 120 m/s, so how to image clearly is an important prerequisite for the defect detection. In [16] the imaging system was equipped with five-line scan CCD cameras to surround the wire rod radially so that its field of view can cover the whole surface at 360°. Besides, the system chose a blue light emitting diode (LED) for lighting to avoid infrared interference from the hot wire rod itself.

Besides, camera should also be equipped with an appropriate lens.

3.2 | Source of light

Light source is an important factor affecting the imaging quality of ASIS. Common light source includes fluorescence, halogen, xenon lamp and LED. Fluorescent light source has the advantages of uniform luminescence, low price and good diffusion, which is suitable for large-area uniform lighting. Halogen light source has high brightness and heating, low price and almost no change in brightness and colour temperature. LED has many advantages, such as long service life, small volume, low power consumption, fast response, high reliability, uniform and stable light and easy integration, so it has been widely used in steel surface defect detection.

3.3 | Imaging method

Two imaging methods are commonly used in ASIS, namely, intensity imaging and range imaging [17]. The steel surface image is usually grey images, that is, grey-level intensity imaging. Range imaging is only for surface defects with 3D characteristics, which provides height information [8]. Range imaging is not affected by the reflection change of steel surface. However, the depth or height information obtained from the image reduces the detection efficiency, and the image resolution is not high, so it is usually used in occasions where the production speed is not high and the 3D characteristics of defects are obvious, such as continuous casting slab and rail. At present, intensity imaging is still used by most steel surface defect detection systems.

3.3.1 | Intensity imaging

Intensity imaging usually has includes bright field lighting and dark field lighting. For bright field lighting, the light source and camera are placed on the same side of the steel, and the reflection angle of the light is equal to the incident angle. For dark field lighting, the light source and camera are also on the same side of the steel, but the reflection angle of the light is no longer equal to the incident angle.

It is often a combination of bright field and dark field lighting to image acquisition for the steel surface defect. Wu et al. [15] used dark and bright illumination simultaneously to collect hot rolled strip images. Liu et al. [18] established an image acquisition system based on bright and dark illumination to detect micro-deformation defects of steel plate surface. Wei et al. [19] proposed a bright–dark field lighting mode to detect defects on the surface of strip steel, and increased the amount of defect information.

In addition, Juan et al. [20] used stroboscopic light and diffusing screens for illumination on stainless production lines, which were placed in a slide and can be displaced transversally to the sheet movement.

3.3.2 | Range imaging

The 2D characteristics of surface defects of some steels (such as continuous casting slab and rail) are similar, but the depth information is quite different, and sometimes it is necessary to get the depth information of defects to judge the quality of steel.

The non-contact 3D measurement has passive measurement and active measurement according to the lighting mode. The passive method does not need a specific active light source, which uses natural light (including indoor controllable lighting source), the 3D information can be reconstructed from the 2D images. Binocular vision is a typical passive way to 3D measurement. Although binocular vision has the advantages of strong adaptability, simple system and low cost, it has complex calculation and low measurement accuracy, so it is less used in steel surface defect detection.

The active method uses a special controlled light source to illuminate the measured surface, and obtains the 3D information of the target. It has the characteristics of high measurement accuracy, strong anti-interference ability and good real-time performance. The representative active measurement technique can be mainly described as structured light, active triangulation, time of flight (TOF), photometric stereo and Moire contouring.

Structured light has been widely used because of its high precision, large field of view and strong real time, including three structures: point, line and surface. Among them, line laser has high speed and measurement accuracy with good monochromaticity, which has been applied in the 3D measurement of steel surface. Ou et al. [21] developed a measurement system combining laser scanning and array CCD to detect the depth of surface defects on continuously cast billet at high temperatures, and achieved an accurate detection in real time. Xu et al. [22] used the laser scanning to detect the surface cracks of high-temperature billet on-line using the high brightness green laser line, and installed a narrow-band colour filter on the lens to remove the radiation light on the surface of high-temperature billet. Xu et al. [23] applied the structured light to carry out the 3D detection of rail surface defects, in which four laser linear light sources and eight area scan CCD cameras were installed around the rail and the depth detection resolution was 0. 2 mm at speed of 1. 5 m/s. Zhang et al. [24] used the sinusoidal phase grating projection method by integrating a grating projector and a CCD camera to measure the depth of continuous casting slab surface cracks. Wen et al. [25] installed two CCD cameras on both sides of the digital light processing (DLP) projector with blue light coded patterns, and used stereo rectification and column-coded patterns to obtain the surface height information of high-temperature steel products.

Based on the optical triangulation principle, the active triangulation method determines the 3D coordinates of each point in space according to the geometric relationship of the distance among the light source (such as laser), the measured object and the camera. Pindor et al. [26] proposed a laser triangulation method to non-destructive testing for continuous casting billets. By analysing the phase shift of projection fringes captured by CCD, the surface defects were detected by parallel laser fringes. Pindor et al. [26] proposed parallel laser fringes to detect surface defects for continuous casting billets by analysing the phase shift of projection fringes captured by CCD.

TOF obtains the distance by measuring the round-trip time of the transmitted signal, which can quickly calculate depth information. TOF has obvious advantages in the case of long measurement distance, however, it is difficult to achieve millimetre accuracy at present. Miyamoto et al. [27] introduced TOF using plane wave to detect defects in billet regardless of the defect position.

Photometric stereo method can also obtain 3D information of image. Kang et al. [28] presented a surface inspection system to detect tiny defects for planar steel surface based on multi-spectral photometric stereo technique. The RGB camera was used to capture colour images of surface illuminated by three light sources at the same time: red, green and blue. Xu et al. [29] applied photometric stereo method to reconstructed 3D model of rail surface with an average relative error of 7. 23%, which can be used for 3D on-line detection of rail surface defects. Shi et al. [30] proposed a measurement system to realize the simultaneous detection of 2D and 3D defects of rail defects, and improved the detection accuracy.

4 | IMAGE PROCESSING ALGORITHM

4.1 | Image pre-processing

4.1.1 | Image denoising

Image denoising usually includes spatial domain methods and transform domain methods. Spatial domain methods include local filtering algorithms and non-local filtering (such as non-local means). Transform domain methods include such as Fourier transform (FT), wavelet transform (WT), Wiener filtering and multi-scale geometric analysis (MGA; Figure 2).

Linear filtering includes mean filtering and Gaussian filtering, which has been widely used in steel surface defect image

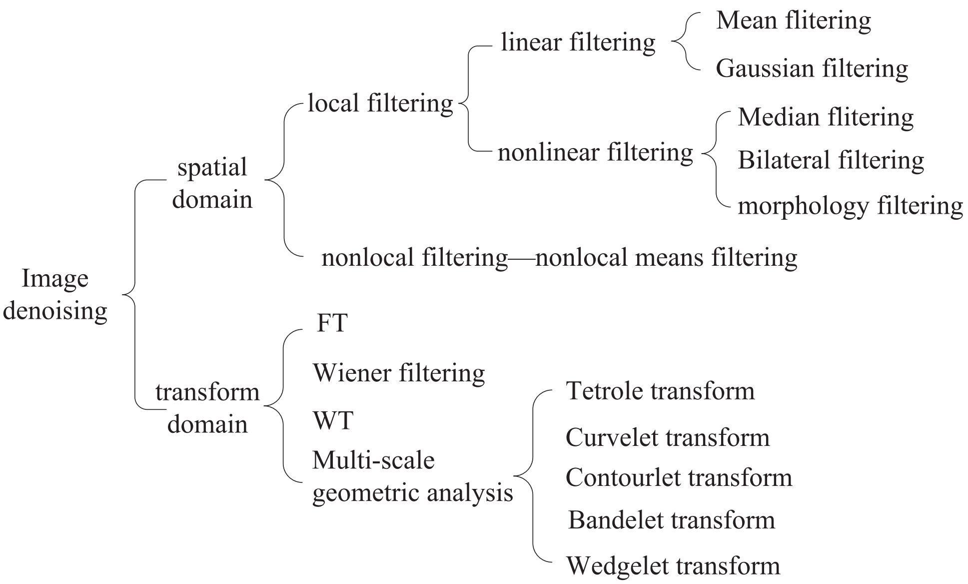

FIGURE 2 Classification of image denoising

denoising [31–36]. The mean filtering is simple and fast, but it cannot protect the image details well. Gaussian filtering can effectively remove Gaussian noise.

Non-linear filtering includes median filtering, mathematical morphology filtering and bilateral filtering. Median filtering has good suppression effect on pulse noise and salt and pepper noise, so it is often used in denoising of steel surface defect images. The basic morphological operations include corrosion, expansion, opening and closing, and the structural elements have an important impact on the morphological denoising effect. Ye et al. [37] performed median filtering and morphological operation on the aluminium strip surface defect image of defect region to remove noise. Yang et al. [38] used morphological processing to denoise the image and clean small-size components after image segmentation. Bilateral filtering considers the spatial information and grey similarity of the image, and retains the edge while removing the noise. Bilateral filter is simple and non-iterative. It preserves the edge of the image, but it will damage the texture of the image to a certain extent. Shi et al. [39] used bilateral filtering to the surface defect on cold rolled aluminium sheet, and then used median filtering to remove strong noise constructed by a regional similarity model.

Non-local means filter is a kind of spatial domain methods. The current pixel value of the image in this method is obtained by weighted average of the pixels in the image with similar regions. Non-local means filter makes full use of the redundant information in the image, and can maintain the detailed features of the image to a large extent while denoising. However, the selection of parameters requires some experience, and the computational complexity is high.

Wiener filtering is based on the minimum mean square error criterion. This filtering method needs to know some statistical characteristics of image and noise, but these statistical characteristics are often treated as constants for approximate calculation. In [40], a Wiener filtering is applied to reduce noise for steel strip with speeds of up to 6 m/s.

The image filtering method based on FT is to transform the image from the spatial domain to the frequency domain, filter the image spectrum, and then transform the image from the frequency domain to the spatial domain. FT has many good performance, but it does not have the ability of local analysis.

WT can localize the signal in spatial domain and frequency domain, and solve the defect of FT. WT has the characteristics of low entropy, multi-resolution and decorrelation. It is also used to steel surface defect image denoising [41, 42]. A cold rolled strip image filtering method based on wavelet anisotropic diffusion is proposed by [43], which effectively separated the noise between signals and protected image edge.

Although WT can better realize signal-to-noise separation, it cannot optimally represent singular high-dimensional functions, while MGA provides the optimal representation of linear and surface singular high-dimensional functions.

In the past 20 years, MGA such as Bandelet [44], Curvelet [45], Contourlet [46] and Tetrolet transform [47] have achieved success in image denoising. The denoising thresholds of these algorithms have a great impact on the acquisition of the optimal direction and the denoising effect. At present, they are not widely used in the denoising of steel surface defect images [48].

MGA usually has the characteristics of multi-resolution and time-frequency localization of WT, as well as good directivity and anisotropy. However, the computational complexity and self-adaptability of MGA need to be improved.

In addition, partial differential equation has the characteristics of anisotropy and is also used for image denoising. Li et al. [49] denoised the strip surface image based on partial differential equation, and the edge of the image is also protected.

4.1.2 | Image enhancement

Due to the illumination conditions, environmental vibration, acquisition instruments and other factors, as well as the different reflection and absorption of light on the steel surface, the illumination of the image is often uneven. Therefore, it is often necessary to correct the non-uniform illumination of the image, which methods mainly include histogram equalization (HE), Retinex algorithm, top-hat transform and homomorphic filtering.

HE is simple in principle and easy to realize, but it is prone to overenhancement and block effect.

The Retinex model proposed by E. H. Land considers that the image is formed by the joint action of incident light and reflected light. If the illumination component is extracted independently, the brightness of the image can be adjusted. Vorobel et al. [50] and Nand et al. [51] developed of Retinex method to remove non-uniform illumination for steel surface images. This algorithm is effective, but the calculation is complex.

Homomorphic filtering can also be used to enhance low contrast images, but there is also the problem of over-enhancement. Zhao et al. [52] proposed a homomorphic filtering based on partial differential equation to revise image's illuminance heterogeneity and obtained better effect. Tang et al. [53] combined WT with homomorphic filtering to enhance the image of small defects on steel strip providing good conditions for image segmentation.

Grey transformation can also be used to adjust the uneven illumination of the image. This method can enhance the ROI in the image, increase the dynamic range of the image and have various forms and flexible applications. In [38], image enhancement was carried by transform greyscale or increasing base value. Zhang et al. [54] proposed an illumination equalized method based on the grey mean of image columns for billet defect images. In addition, Yun et al. [16] applied a discrete WT to reduce the non-uniformity of steel wire rod images.

4.2 | ROI detection

ROI detection is to quickly determine whether there are surface defects in an image, and real-time and robustness are the main considerations for online detection. At present, background subtraction method is commonly used for ROI detection [15, 55], which subtracts the target image from the reference one to obtain the contrast image, and then judges whether there is a defect according to a threshold. This method is simple to calculate, but its effect depends on the reference image and threshold.

Wu et al. [15] used region growing method to find out defect areas by merging suspicious pixels. Li et al. [36] detected ROI for steel bar based on local annular contrast with high speed and accuracy. Wang et al. [56] proposed an algorithm of greyscale projection overcoming the dependence on reference image, but the effect will be disturbed by noise. Zhang et al. [48] detected ROI by vertical projection and grey contrast algorithm for railway surface defects. Some other ROI search algorithms were proposed in [12, 39, 57–59].

4.3 | Image segmentation for ROI

The purpose of image segmentation for ROI is to separate surface defects from image background to extract the feature. Image segmentation algorithms include threshold, edge detection, region segmentation, clustering method and method based on specific theory.

4.3.1 | Threshold method

Threshold method divides image pixels into several categories by setting threshold. Because of its simple implementation, small amount of calculation and stable performance, it has been widely used in image segmentation, especially suitable for images with different target and background greyscales. Threshold will directly affect the effect of image segmentation. The commonly used threshold methods include fixed threshold method, histogram method and adaptive threshold method.

The fixed threshold method has high speed and is suitable for the case of obvious difference between image background and target. The difference between steel surface defect and the background is not obvious, so the fixed threshold method is not effective here. In addition, since there are no obvious double peaks in steel surface defect images, the effect of histogram method to image segmentation is often not good either.

The adaptive threshold algorithm calculates the local threshold according to the grey distribution of different regions of the image. Juan et al. [20] used a histogram threshold based on the integration of empirical knowledge for residual oxide scale detection in stainless steel production. Nand et al. [51] introduced histogram thresholding method for image segmentation and tested on three kinds of steel surface defects, that is, water droplet, blister and scratch successfully. Neogi et al. [60] developed a global adaptive percentile thresholding of gradient image for steel strip defects detection, which adaptively changes the thresholding according to the number of pixels above certain grey values in gradient images. In [16], the dual-adaptive threshold binarization method is adopted and good detection results are achieved. Otsu method is a typical adaptive threshold method, which determines the threshold dynamically by maximizing variance between the target and the background, as shown for steel surface defects in [55]. Zhang et al. [54] presented particle swarm optimization (PSO) algorithm to get the binarization threshold of Otsu for partitioned billet images effectively. Otsu is simple to calculate, but sensitive to noise and target size.

Two-dimensional Otsu algorithm [61] uses image grey value and neighbourhood average grey value as two dimensions to perform threshold segmentation, which improves the anti-noise performance and segmentation effect. MA et al. [62] used two-dimensional Otsu algorithm to efficiently segment the defects of cold rolled thin strip with low contrast and complex noise.

The information entropy is also applied to image segmentation [63]. Yen et al. [64] used the maximum correlation principle to replace the commonly used maximum entropy principle to select the threshold. Sharifzadeh et al. [65] chose Renyi entropy to segment rust defects of steel surface, with an accuracy of 90.3%. These methods are seldom used in the image segmentation of steel surface defects due to the large amount of calculation.

4.3.2 | Edge detection method

The discontinuity of grey of edge pixels can be detected by derivation. The first derivative edge detection operators mainly include Roberts, Sobel, Prewitt and Kirsch, and the second derivative operators mainly include Laplacian, LoG (Laplacian of Gaussian), DoG (Difference of Gaussian) and Canny [66].

Roberts is accurate in edge location, but it is also sensitive to noise. Sobel can suppress noise to some extent, but the edge location accuracy is not high. Liu et al. [59] used Sobel method to steel surface defects detection with the detection rate of 80%. In order to improve detecting accuracy for surface defects inspection on heavy rails, an improved Sobel operator is developed by adding the templates with directions of 45°, 135° in [30], which gained more comprehensive edge information than the original Sobel. Kirsch has good effects in maintaining details and anti-noise, but the amount of calculation is large. Tang et al. [67] selected four of the eight templates of Kirsch to simplify the calculation, which had little impact on the effect of edge detection. Choi et al. [32] used edge detection filtering based on the first-order derivative to detect vertical scratch defects on bar, and then, the double threshold method was performed to binarize the image and edge pair search algorithm was proposed to reduce pseudo defects.

Laplacian operator has rotation invariance, but it is sensitive to noise. Although LoG overcomes the influence of noise to some extent, it may produce false edges and cannot detect sharp edges. DoG is the difference of Gaussian functions at different scales, and its computational complexity is lower than LoG. Yun et al. [68] proposed a detection algorithm based on Laplacian operation, edge-preserving filtering and double thresholding method to real-time defect detection for steel bar in coil and detection rate of 95.42% was reported. Canny achieves the best compromise between noise suppression and accurate edge detection. Canny was used to locate all possible crack edges in the surface image of steel slab [69] and edge detect for hot rolling process surface defects [70].

4.3.3 | Region segmentation method

Region segmentation method is to form regions according to the similarity characteristics of pixels, mainly including region growth, split-merge and watershed method.

Region growth method does not need use a priori knowledge, and the image segmentation effect mainly depends on the selection of seed points, growth criteria and termination conditions. Region growing was used for segmentation of steel surface defect image in [71–74]. It is usually used in occasions with low real-time requirements because of the large amount of calculation. Jaffery et al. [75] compared four rail head image segmentation algorithms, namely, region growth, watershed segmentation, K-means clustering and Canny edge detection, and showed that region growth had higher accuracy than the other three methods.

Watershed algorithm is an image segmentation method based on topology theory. It has a good response to weak edges, but image noise and the subtle grey change will produce over-segmentation. Chu et al. [76] used watershed algorithm to segment steel plate surface defects, and the results showed that the watershed algorithm had good segmentation effect on six kinds of defects.

4.3.4 | Clustering segmentation method

Clustering segmentation gathers the pixels with feature similarity into the same region, iterates repeatedly until convergence and finally gathers all pixels into different categories to realize segmentation. These algorithms usually include mean shift, K-means, fuzzy c-means (FCM) clustering and so on.

Mean shift was presented to segment the defects in strip images in [77]. Saeedi et al. [78] proposed a method based on morphological reconstruction and mean shift filtering to detect defect for electrical discharge machined steel. Mean shift has good stability and robustness, but it is seldom used in online detection of steel surface defects due to its complexity of calculation.

K-means is simple and widely used, however, the number of clusters must be given in advance. The initial clustering centre point will also affect the image segmentation effect, and the clustering result is easy to be affected by image noise.

Compared with K-means algorithm, FCM clustering results are more flexible. FCM is sensitive to the initial clustering centre and easy to fall into the local optimal solution. Chaudhari et al. [79] adopted FCM and level set methods to accomplish segmentation for crack detection in a railway track.

4.3.5 | Segmentation method based on specific theory

Mathematical morphology, WT, artificial neural network (ANN), genetic algorithm (GA) [80] and algorithm based on fuzzy theory are also applied to image edge detection methods.

WT has good localization properties in both time domain and frequency domain, which has been applied to the segmentation and detection of steel surface defects [43, 81–84].

Mathematical morphology is effective and accurate in image segmentation, but it is sensitive to noise. The mathematical morphology algorithm with multi-structural elements can not only extract small edges, but also suppress noise. Morphology used to image segmentation for steel surface defects has many instances, such as [38, 55, 85-88]. Tang et al. [89] studied the edge detection of strip surface defect by using the mathematical morphology of multi-structural elements, and effectively detected the edge of weak and small targets.

GA is an optimization algorithm proposed by John H. Holland according to biological evolution and genetic variation theory. Liu et al. [90] used mathematical morphology to reduce the non-uniform illumination, and binarized the strip steel defects image based on GA.

Besides, Zhang et al. [48] used an improved Gaussian mixture model based on Markov random field (MRF) to railway surface defect segmentation accurately. Xu et al. [91] introduced hidden Markov tree (HMT) model that realizes multi-scale defect segmentation with an accuracy of 94.4%, and the context-adaptive HMT was introduced to fuse the segmentation results of different scales with the false rate of 3. 7%.

4.4 | Feature extraction and selection

The commonly used image features mainly include texture, transform domain, shape and grey-level features.

4.4.1 | Texture features

Texture is an important feature of image representation. It does not depend on colour and brightness, and has resistance to noise.

Statistical method

Statistical method regards texture as a random phenomenon and analyses the distribution of random variables from the perspective of statistics, mainly including grey-level co-occurrence moment (GLCM), local binary pattern (LBP) and histogram of oriented gradient (HOG).

GLCM is a common statistical method based on the spatial distribution information of pixels. In order to reduce the amount of calculation and improve the accuracy of feature classification, contrast, correlation, energy and homogeneity are often taken as its features. Xu et al. [22] decomposed the slab surface image by undecimated wavelet to calculate the scale co-occurrence matrix of the low-frequency component and GLCM of high-frequency component as the texture feature of the image. Guo et al. [92] showed GLCM can describe the texture information of strip image and classify four kinds of defects effectively. In [93], gradient magnitude and gradient orientation co-occurrence matrix (GMGOCM), along with grey level and gradient orientation co-occurrence matrix (GLGOCM), was proposed to realize scale and rotation invariance in defect feature extraction.

HOG constructs the features by calculating and counting the gradient direction histogram of the local area of the image. It can capture local shape information and has good invariance to geometric and optical changes, but has a high dimension and a large amount of calculation. Wang et al. [94] fused HOG and GLCM to an improved random forest algorithm with optimal multi-feature-set fusion with a recognition accuracy of 91%.

LBP uses binary bits to express the relationship between local neighbourhood points and central points, and the binary bits of all neighbourhood points are used to describe local structure information. LBP has rotation invariance, multi-scale, simple calculation and robustness to image grey changes caused by illumination changes. Therefore, LBP has been applied to steel surface defect detection [95–98]. Guo et al. [99] proposed a complete local binary pattern (CLBP) to extract features that are comprehensive and have strong discrimination ability. However, this method is still sensitive to Gaussian noise. Song et al. [100] proposed a noise-robust method of adjacent evaluation completed local binary patterns (AECLBPs) for hot-rolled steel strip surface defects recognition, which constructed a neighbourhood evaluation window around the neighbourhood to modify the threshold scheme of the CLBP. Chu et al. [101] proposed smoothed local binary pattern (SLBP) with the ability of noise smoothing to feature extraction for strip steel surface defect images which was determined by the sign of the difference between weighted greys in local neighbourhood. Luo et al. [102] proposed a generalized completed local binary pattern (GCLBP) excavating the description information hidden in non-uniform patterns and obtained a better description of feature for steel surface defect. In addition, Samadani et al. [103] extracted nine statistical features to defect classification for high-speed steel bar in coil.

Statistical method is simple and easy to realize, especially GLCM has strong adaptability and robustness. However, this method lacks the global information of the image, and it is difficult to find the pixel dependence between texture scales.

Structural method

Structure method is based on the theory of texture elements. It is considered that complex texture is composed of some texture elements that appear repeatedly in space according to certain rules. The characteristic parameters of elements include area, perimeter and eccentricity, and the structural parameters are determined by the arrangement law between elements. In more complex cases, they can be obtained by syntactic analysis, mathematical morphology and so on. Jeon et al. [82] used four morphological features (area ratio, compactness, roughness and orientation) to distinguish corner cracks from scales on the surface of steel billet.

However, the structure method is only suitable for images with large texture elements and regular arrangement. For general natural texture, it is difficult to describe accurately because of its strong randomness and large structural changes, so it should be used in combination with other methods.

Model method

Model method uses the statistics of model parameters as texture features. Different textures show different values of model parameters under certain assumptions. Typical model methods include fractal model, MRF, Gibbs and auto regressive model.

Fractal dimension is an important description of texture. A fractal is a shape composed of parts similar to the whole to some way, and fractal model is mainly applicable to natural textures with self-similarity. The distribution of steel plate surface defects can be regarded as a random irregular phenomenon, which is suitable to describe by fractal dimension. It was used to describe the characteristics of steel surface defects and obtained good results in [40, 104, 105].

Model method considers not only the randomness of local texture, but also the regularity of the whole texture. However, it is difficult to estimate the parameters of the model, and the amount of calculation is large.

4.4.2 | Transform domain features

Transform domain features are based on time domain, frequency domain or multi-scale analysis. The main algorithms are FT, Gabor filter, WT and MGA.

FT

FT is to transform the image from spatial domain to frequency domain, and use spectral energy or spectral entropy to express the texture. Xu et al. [106] obtained the amplitude spectrum of the sub-image by FT, and then obtain the invariant moment of the amplitude spectrum image as the feature quantity, which not only has translation and rotation invariance, but also has the advantages of anti-noise and suppression of uneven illumination. However, FT does not have local analysis capability.

Gabor transform

In order to overcome the disadvantage of FT that cannot be analysed locally, short-time Fourier transform (STFT) is proposed by adding a window function. Gabor transform takes Gaussian function as window function. Cong et al. [107] effectively extracted the texture features of strip steel surface defects by using Gabor filter, and used the evaluation function to maximize the energy response difference between defect and defect free image to determine the best parameters of the filtering. In [108], Gabor wavelet was used to decompose the surface defects image on hot-rolled steel plates into 40 components in five scales and eight directions, and then the means and variance of real and imaginary parts of each component and the original image were extracted, respectively, to obtain a 162-dimensional feature vector. Yun et al. [109] presented an effective defects detection algorithm based on Gabor filters optimized by GA for defects detection of billet surface and showed good performance.

Gabor filter has a good effect in texture description. Because the window function determines the locality of spatial domain, Gabor transform also has locality in frequency domain. At the same time, there is a problem of large amount of calculation.

WT

Although STFT improves this limitation to a certain extent, the sliding window function used is fixed once selected, so its time-frequency resolution is fixed too, and WT can solve this problem.

The texture of an image is often characterized by multi-scale features. After wavelet decomposition, a series of images with different resolutions are obtained; the image of each resolution is composed of a series of high-frequency sub-band images representing different direction information. WT has been widely used to extract image features for steel surface defect detection [58, 110, 111]. Wavelet basis of WT will affect the effect of image texture analysis. Ghorai et al. [112] evaluated the performance of different wavelets (Harr, DB2, DB4, biorthogonal spline) at different decomposition levels, and showed that the three-level Haar feature set was suitable to 24 types of defects detection for hot-rolled steel surface.

MGA

Wavelet analysis cannot sparsely represent the geometric characteristics of signal high singularities. MGA has anisotropic characteristics and can effectively represent line singularity and surface singularity in high-dimensional data space.

Krommweh [47] constructed a new multi-scale directional transform of Tetrolet, which expressed more abundant and accurate image information. Xu et al. [113] decomposed the surface image of hot rolled steel plate into sub-bands with different scales and directions through Tetrolet transform, and then extracted the Tetrolet high pass coefficient matrix features of sub-bands to obtain a high-dimensional feature vector. In [114], the image was decomposed by Shearlet transform to obtain many sub-bands, and then the geometric, statistical, texture and other features were calculated from the sub-bands for classification of surface defects. Xu et al. [115] proposed an adaptive MGA called RNAMlet to test on images of three kinds of steel (continuous casting slab, hot rolled steel plate and cold rolled steel strip), and compared with Contourlet, Shearle and Tetrolet, showing that the defect recognition rate was higher than that of the other three methods.

4.4.3 | Shape features

Shape features can be divided into two categories of region based and contour based.

Region-based shape features

Region-based shape features used the parameters to describe the properties of the region surrounded by the target contour, mainly including geometric, topological and moment features.

Geometric features include simple description of regional features, such as area, perimeter, centroid, dispersion, rectangularity and aspect ratio; it also includes features based on shape similarity, such as rectangularity, circularity, eccentricity and perimeter ratio.

Moment can be used to describe the characteristics of grey image. The common moment features include geometric moment, orthogonal moment and complex moment. The geometric moment is proposed by Hu [116], which has translation, rotation and scale invariance. Moment invariants were widely used as defect features of steel surface images [30, 76, 106, 117]. The low-order geometric moments of Hu invariant moment do not contain much image detail information, while the high-order geometric moments are vulnerable to noise. Zernike moment can construct any higher order moment, which has rotation invariance and is not sensitive to noise, but it has no translation and scale invariance, and the calculation is complex.

In addition, the scale invariant feature transform (SIFT) is invariant to the changes of rotation, scale and brightness. SIFT was used to extract the feature vector, with a recognition rate of defects on the surface of moderately thick plates reaching 95% [118]. Suvdaa et al. [119] also used SIFT for defect regions detection and features extraction to steel surface defects.

Contour-based shape features

This method obtains the shape parameters of the image by describing the contour features, in which Hough transform and Fourier descriptor are widely used.

Hough transform is one of the basic methods to identify geometric shapes from images in image processing to detect shapes such as lines, circles and parabola in images. Martins et al. [33] used Hough transform to classify three kinds of surface defects on rolled steel with classification accuracy rate of 98%. Hough transform is not sensitive to discontinuities and noise, but the time complexity and space complexity are high.

Fourier descriptor uses the FT of the target boundary as the shape feature, which has translation, rotation and scale invariance after normalization. Hu et al. [120] used five typical shape features, namely, rectangularity, density, slenderness, Hu invariant moment and Fourier descriptor to describe the features of steel plate surface defects. Ref. [121] extracted three kinds of image features, namely, geometric features, grey features and shape features, in which Fourier descriptors and moment descriptors were taken as shape features.

4.4.4 | Grey-level features

The histogram of an image reflects the probability of the occurrence of image grey level and provides a lot of information of the image. The commonly used grey-level features include: maximum value, minimum value, mean value, median value, value range, variance and entropy.

Histogram feature calculation is simple and has translation and rotation invariance. It has been widely used in feature extraction of steel surface defect images [52, 55, 76, 122, 123].

4.4.5 | DL-based features

DL is very different from traditional pattern recognition methods in that it can automatically learn features from massive data which can contain thousands of parameters rather than manually designed features. The features of manual design mainly rely on the prior knowledge of the designer, and their parameters are very limited. DL can quickly learn new and effective feature representations from training data. He et al. [98] proposed multilevel-feature fusion network (MFN) combining multiple hierarchical features into a feature set with more location details of defects, and reached 82.3 mAP on ResNet50 using 300 proposals on the NEU-DET.

The image feature types of steel surface defects based on image processing are shown in Table 2.

4.4.6 | Feature combination and dimension reduction

There are several methods for feature extraction of steel surface defects, but it is rare that only one type of feature can effectively classify different steel surface defects. It is usually necessary to combine different types of features to form combined features in order to accurately identify different types of defects. Multiple types of features were extracted, such as grey, shape, texture and invariant moment features to express steel surface defects completely [76]. Thirty-eight features comprising greyscale, shape, texture and geometric features were extracted for steel surface defects classification [120]. In [122], the features based on co-occurrence matrix, invariant moment, inertia moment and grey standard deviation were integrated into a feature vector to distinguish the normal textures from abnormal ones of flat surface product. Choi et al. [123] extract 54 features including 46 geometric features (such as length, area, orientation and centre of mass in pixels) and 8 grey-level features for rolling strip surface inspection. Chen et al. [124] extracted 49 features, including 18 geometric features, 20 grey-level features, 7 texture features based on GLCM and 4 projection features for real-time steel inspection system. In [125], total of 27 features made up of geometric, grey and projection features extracted to identify steel plate surface defects.

Different features have their advantages and disadvantages; therefore, these different types of features usually should be combined in an appropriate way. It is desirable that the combined features are not related to each other and should be distinct from each other.

In order to determine the weight of multiple features in the classification and properly combine them, an improved random forest with optimal multi-feature-set fusion (OMFF-RF) algorithm was proposed for distributed defect recognition [94]. Hu et al. [125] calculated information entropy corresponding to each defect and used information entropy to rank all extracted features to select the most appropriate ones. In [126], three feature selection methods, namely, correlation-based feature selection, consistency subset evaluator and information gain, were used to optimize the feature space and showed good robustness and effectiveness for steel strip surface inspection.

Relief is a feature weighting algorithm that assigns different weights to features according to the correlation between each feature and category, and removes features whose weights are less than a certain threshold. ReliefF is an extension of Relief, which can deal with multiple types of data. Gong et al. [127] used ReliefF to obtain weight parameter representing the importance degree of feature for strip steel surface defects, and then

TABLE 2 Feature types of steel surface defect

Type	Methods	Ref.	Advantages	Disadvantages
Texture features	GLCM	[22, 92, 93]	Has strong adaptability and robustness.	Difficult to find the pixel dependence between texture scales.
	HOG	[94]	Has good invariance to geometric and optical changes.	Be of a high dimension and a large amount of calculation.
	LBP	[95–102]	Has rotation and grey invariance.	Sensitive to scale variation and noise.
	Morphology	[81, 103]	Suitable for random or natural texture with low computational complexity.	Difficult to describe it accurately because of its strong randomness and large structural changes.
	Fractal Model	[43, 104, 105]	The whole information of image can be expressed by partial features.	Mainly applicable to natural textures with self-similarity.
Transform domain features	FT	[106]	Has translation and rotation invariance.	Without local analysis capability.
	Gabor transform	[107–109]	Has a good effect in texture description.	Has locality in frequency domain.
	WT	[22, 58, 110-112]	Can meet the requirements of time-frequency signal analysis and focus on any details of the signal.	Difficult to select wavelet basis.
	Tetrolet	[113]	Has more abundant directional components than wavelet transform and can represent the original image sparsely.	Has high computational complexity.
	Shearlet	[114]	Has good sparsity and locality.	The detailed information of the original image cannot be effectively protected.
	RNAMlet	[115]	Has multi-resolution characteristics and time-frequency localization characteristics, and has good directionality.	Adaptability needs to be improved.
	Moment invariant	[30, 76, 106, 117]	Has translation, rotation and scale invariance.	The low-order invariant moment do not contain much image detail information.
	Hough	[33]	Be of not sensitive to discontinuities and noise.	Can only detects defects of specific shapes, and has high complexity.
	Fourier descriptor	[120, 121]	Has translation, rotation and scale invariance after normalization.	Sensitive to noise and deformation.
Grey-level features	Maximum value, minimum value, mean value, median value, value range, variance and entropy	[52, 55, 76, 122, 123]	Be of simple and has translation and rotation invariance.	Effective combination requires a certain amount of experience and time.

proposed a multiple support vector hyper-sphere with feature and sample weights to realize multi-class classification.

On the other hand, multi-dimensional feature data is likely to contain a large amount of redundant information. Therefore, it is generally necessary to reduce the dimension of features. At present, feature dimension reduction algorithms mainly include principal component analysis (PCA), GA, locality preserving projection (LPP), linear discriminant analysis (LDA) and independent component analysis (ICA).

PCA is a linear combination method, which is widely used in feature dimension reduction of steel surface defects [33, 122, 128, 129]. This method is simple, however, in many cases, the features are non-linear. Kernel principal component analysis (KPCA) achieves linear dimension reduction by introducing kernel function to map linear inseparable data sets to higher dimensional space.

GA is also commonly used to optimize features. Wu et al. [15] used GA as feature extraction and optimization method for online surface inspection system of hot rolled strips. In [120], four types of visual features formed a 38-dimensional feature vector, from which 14 features were selected by GA to be trained in the SVM model. In [130], a 32-dimensional feature vector was optimized for dimensionality reduction by GA, and 20 of them were selected for defects classification, and the result showed that the dimension reduction effect of GA is roughly equivalent to that of PCA, but the processing speed of the latter is slightly slower.

Kernel locality preserving projection (KLPP) was also applied to the features dimension reduction of steel surface defects [108, 113]. A high-dimensional feature vector was reduced to a low-dimensional one by KLPP [131], and multi-scale feature extraction method was implemented via Curvelet transform and KLPP [132].

LDA is also used for feature selection. Cord et al. [133] used LDA for linear combination of initial features to maximize the ratio of inter-class variance to intra-class variance.

Since the encoded dimension is generally much smaller than the input data, AutoEncode can also be used to reduce feature dimension. He et al. [134] adopted AutoEncoder to reduce the dimension of multi-scale features of hot rolled steel surface inspection, which improved the generalization ability of insufficient training samples.

4.5 | Defect classification

The classification of steel surface defects can be classified into unsupervised, semi-supervised and supervised classifier. Unsupervised learning only needs to use unlabelled samples, supervised learning needs to use labelled samples while semi-supervised learning uses a large number of unlabelled samples and a small number of labelled samples.

4.5.1 | Unsupervised classifier

Clustering is an unsupervised classification method, and K-means is a typical clustering algorithm. K-means uses distance as the similarity evaluation, but its result is easy to be affected by noise. Cohn et al. [135] used K-means clustering to classify six different surface defects on hot-rolled steel and achieved accuracy rate about 99.4%.

Self-organizing maps (SOM) is a competition-based unsupervised learning algorithm. SOM and PCA were used to classify three defects with complex shapes, namely oxidation, exfoliation and waveform defect, and an overall classification rate of 77% was achieved [33]. Wang et al. [136] presented a fast, simple and robust classifier of Winner Trace Marking based on SOM and obtained satisfactory results.

Rough set (RS) is a mathematical tool to deal with fuzzy and uncertain knowledge, which provides a systematic method to find rules from small sample data. Tang et al. [137] classified the strip surface defects based on RS and compared it with BP and verified the effectiveness of RS. Both the theory of fuzzy sets and RS are similar in dealing with uncertain and fuzzy problem, thus the fuzzy-rough sets were established for automatic delineation of the 3D ROI shape [12].

At present, unsupervised learning based on DL mainly includes AutoEncoder and restricted Boltzmann machine (RBM). Lv et al. [138] proposed an improved denoising AutoEncoder network for rod surface defects detection combining ReLU and BN (batch normalization) layer, and obtained network weights through unsupervised pre-training and supervised fine-tuning, which achieved an average accuracy rate of 99.1%.

Generative adversarial network (GAN) is a DL model and can be used as unsupervised learning. Liu et al. [139] proposed the GAN-based classification for strip steel surface defects, reaching an average accuracy of 94% in the data sets.

4.5.2 | Semi-supervised classifier

Semi-supervised learning is a combination of supervised learning and unsupervised learning. CNN can be used not only for supervised learning but also for semi-supervised learning. Gao et al. [140] proposed a semi-supervised learning method based on CNN for steel surface defect recognition under limited labelled samples with an accuracy of 90.7%. Zheng et al. [141] proposed a generic semi-supervised DL-based approach for automated surface inspection, which used a new loss function calculation method and a residual CNN to achieve accurate defect detection. He et al. [142] proposed a semi-supervised learning method using multi-training of the deep convolutional GAN to generate new samples and applied Resnet18 to the steel surface defect classification effectively. In [143], CAE-SGAN was proposed based on convolutional autoencoder (CAE) and semi-supervised generative adversarial networks (SGAN), and the classification rate of hot rolled plate increased by about 16%.

Semi-supervised method is mainly used for defect classification rather than the localization and segmentation of defect.

4.5.3 | Supervised classifier

ANN

ANN has many advantages, so it is widely used in the fields of information processing, pattern recognition and so on.

D. E. Rumelhart BP (proposed error back propagation) algorithm, which solved the learning problem of hidden layer connection weight of multilayer neural network. BP-ANN has strong non-linear mapping ability, so it has been used to identify steel surface defects and obtained good classification results [30, 38, 55, 103]. However, the learning speed of BP-ANN is not fast, there is no perfect method to determine the network layer and the number of neurons, and it is easy to fall into the local minimum.

Radial basis function (RBF) neural network has good generalization ability and fast learning convergence speed. Han et al. [144] used the quantum particle swarm optimization radial basis function (QPSO-RBF) to classify strip defects with average recognition rate of 94.63%. Xu et al. [106] used the amplitude spectrum and moment invariants as feature quantities and LVQ as classifier to classify the surface defects of medium and heavy plates, and the recognition rate was 81.5%

Currently, researchers have started to use CNN and DL to detect steel surface defects and learn defection-related features directly from a large number of training samples, rather than using hand-designed features like traditional classification methods. Yi et al. [145] adopted end-to-end CNN to classify seven types of strip steel surface defects, using symmetrical surrounding saliency map and defect image as input while defect categories as output. Huang et al. [146] proposed a deep neural network to automatically distinguish six kinds of hot-rolled steel strip surface defects, and the results showed that the accuracy, precision and area under curve (AUC) reached 99.5%, 99.51% and 99.98%, respectively.

However, sometimes it is difficult to obtain a large number of defect samples for CNN, thus Kim et al. [147] adopted few-shot learning with Siamese neural network using CNN structure to classify steel surface defects with a small number of defect samples.

The task of object detection is to find out all the objects of interest in the image and determine their categories and positions. Object detection based on DL can be divided into two types in terms of network structure: One is two-stage network based on region proposal, such as Faster R-CNN [148]; the other is one stage network represented by SSD (single shot multi-box detector) [149] and Yolo (you only look once) [150] and its series. The former divides the detection problem into two stages, first generates candidate regions, and then classifies the candidate regions; the latter directly uses the features extracted from the network to predict the location and category of defects. Wei et al. [151] proposed a defects detection method based on Faster R-CNN, and showed that the detection rate can reach 97% in real industrial environments. Lin et al. [152] proposed a DL method to detect defects, which used SSD to learn possible defects and ResNet to classify three types of defects on the steel surface. Li et al. [153] used improved YOLO consisting of 27 convolution layers to detect six types of steel strip surface defects, and its mAP (mean average precision) and recall rate reached 97.55% and 95.86%, respectively, as well as the detection rate reached 99% at 83 fps.

Generally speaking, a two-stage algorithm has advantages in accuracy, while a one-stage algorithm has advantages in speed. How to better balance accuracy and speed has always been an important direction of target detection algorithm.

In recent years, DL has achieved great success in classification and location for object detection, and has also been applied to semantic segmentation and instance segmentation.

Fully connected network (FCN) [154] is the basic framework of semantic segmentation. Many semantic segmentation methods are based on the improvement of FCN, such as Unet and SegNet, both of which adopt encoder–decoder structure. R-CNN [155] series is also a common method of image instance segmentation.

Xian et al. [156] proposed a cascaded Autoencoder for metallic surface defect location and segmentation, and the segmented defect areas were classified by CNN. Zhang et al. [157] developed an SGAN with two sub-networks (the segmentation network and fully convolutional discriminator network) for precise segmentation results at the pixel level. Huang et al. [158] employed a depth-wise separable U-shape network, in which depth-wise separable convolution was employed to replace the traditional convolutional layer to accelerate the segmentation performance, and a multi-scale module was proposed to extract multi-scale context and the segmentation accuracy was improved. Chen et al. [159] selected Faster R-CNN as the fundamental framework to detect various surface defects of aluminium alloys and gained good performance.

However, segmentation methods based on DL such as Mask R-CNN consume a lot of computing resources and are difficult to meet the real-time requirements of industrial applications at present. In addition, it is difficult to build a large instance level defect segmentation data set [160]. Unlike the above-mentioned methods, He et al. [160] established an end-to-end steel surface defect detection system, which can provide a bounding box with a class score for precisely classifying and locating defects.

Bayesian classifier

Bayesian classifier uses Bayesian formula to calculate posterior probability according to prior probability, and select the class with the maximum posterior probability as the class to which the object belongs. Pernkopf [161] used Bayesian network classifier to detect raw steel blocks surface defects, whose structure was determined by floating search algorithm, and the classification accuracy rate was 98%.

Bayesian classification can give strict mathematical proof, which is intuitive and simple, but the prior probability of samples is generally difficult to determine.

K-*nearest neighbour (KNN)*

KNN is an intuitive machine learning method, and its basic idea is that if most of the k nearest samples in the feature space belong to a certain category, the sample also belongs to this category.

KNN method is easy to understand and implement without estimating parameters. It has been applied in steel surface defect classification and surface quality evaluation [162, 163]. Mentouri et al. [164] used the KNN combining with binarized statistical feature extractor to efficiently recognize strip surface defects in the hot rolling process.

However, KNN requires a lot of computation because it needs to calculate the distance from unknown samples to all known samples.

Support Vector Machine (SVM)

SVM adopts the principle of structural risk minimization (SRM) to map the input space of samples to high-dimensional feature space, so as to achieve linear separability. On the basis of binary classification of SVM, there are usually two methods to construct multi-class SVM: one-versus-rest and one-versus-one.

SVM shows many unique advantages in solving small sample, non-linear and high-dimensional pattern recognition, and has been widely used in steel surface defect detection [16, 18, 113, 121, 123, 124, 128].

Although SVM shows good effectiveness and robustness in pattern classification, its computational complexity is high. Twin support vector machine (TWSVM) [165] and least squares support vector machine (LSSVM) [166] reduced the computational complexity while maintaining the small sample learning ability and anti-interference ability. Chu et al. [76] proposed a multi-class classification method based on TWSVM and extended it by using multiple information mined by KNN to integrate boundary sample information, representative sample information and feature weight information, showing high efficiency and accuracy. Chu et al. [93] adopted LSSVM to realize strip steel surface defect recognition with high efficiency and accuracy.

In addition, SVM is vulnerable to noise and outliers. In order to solve this problem, Lin et al. [167] proposed fuzzy support vector machine (FSVM), which reflects the importance of different samples by assigning corresponding fuzzy membership values to different samples. FSVM reduces the influence of noise and outliers on the final decision function and improves the classification accuracy. Zhao et al. [52] designed defect classifier based on FSVM for cold rolling strip surface defect online inspection and gained better classification effect.

A multiple support vector hyper-sphere with feature and sample weights (FSW-MSVH) was proposed for strip steel surface classification in [127], which can restrain the adverse impact of abnormal samples and weakly relevant features, and improved classification accuracy and speed. Agarwal et al. [168] proposed process knowledge–based multi-class support vector machine (PK-MSVM) to improve the accuracy of classification for surface defects of hot rolling combining feature extraction with the process knowledge, and performed better than traditional multi-class support vector machine (MSVM).

Other classifier

Ensemble learning combines multiple machine learning models to complete learning tasks and improve classification effect. Boosting is one of ensemble learning algorithms combining a series of weak classifiers that depend on each other into a strong classifier. The representative of Boosting algorithm is the AdaBoost (adaptive boosting). Xu et al. [22] used AdaBoost to identify five types of defects and pseudo defects on the surface of high-temperature billet, and the overall recognition rate was 87.16%. Hu et al. [125] proposed a new algorithm based on AdaBoost choosing the BP-NN as the weak classifier by filtering mechanism, and the classification accuracy was 12.91% higher than a single BP-NN.

Random forest (RF) is also a kind of ensemble learning, which is based on the decision tree model under bagging framework. Wang et al. [94] presented optimal multi-feature-set fusion (OMFF-RF) algorithm, which fused the HOG and GLCM feature sets, to identify five types of distributed defects on steel surfaces from an actual steel production line, and achieved a recognition accuracy of 91%, which was better than SVM and conventional RF algorithm.

Various classification algorithms are shown in Table 3.

5 | DISCUSSION AND SUMMARY

The process of steel surface defect detection based on machine vision usually includes image acquisition, image pre-processing, target region segmentation, feature extraction and selection and defect classification. This paper summarizes the visual-based inspection of steel surface defects in recent 20 years, especially in recent 5 years. Discussion and summary follow.

1) Small sample: When using ANN to classify steel surface defects, small samples often cause over-fitting. However, it is often difficult to obtain massive defect samples. The following methods are usually used to deal with the problems caused by small samples.

More samples can be obtained by image amplification. The most commonly used methods of image amplification are to mirror, rotate, translate, scale, add random noise and adjust the contrast of the original sample and so on [141, 169]. Wei et al. [170] generated simulated defects in specified areas of defect-free samples, which can complete the labelling process while augmenting the data set for the few-samples segmentation task studied.

GAN is often used for image generation and enhancement. Jain et al. [171] proposed a framework for data augmentation by creating synthetic images using GAN, and its generator synthesized new surface defect images from random noise is used further for training of classifications.

One-shot learning can reduce the massive data requirements for DL. Deshpande et al. [172] proposed a Siamese CNN to do one-shot recognition for steel surfaces, which can significantly reduce the requirements of training data and can meet the requirements of real-time detection.

Unsupervised and semi-supervised learning can also reduce the demand for massive defect samples [33] [135, 142]. In addition, for small samples, the method of transfer learning can also be used to detect steel surface defects [173].

2) Real-time problem: With the progress science and of technology, the rolling speed of steel production has been greatly improved compared with the past. The modern cold rolling speed of strip steel has reached 45 m/s, while the rolling speed of wire rod has exceeded 130 m/s, which is a challenge to the defect detection of steel surface. For online detection, real time is very important.

When the surface quality of tin steel strip was detected online, the image was transmitted to the image distributor through optical fibre to divert the image data, and then processed by multi-core CPU parallel processing to realize the real-time detection with image data of more than 200 MB/s.

Wen et al. [25] applied GPU (graphics processing unit) to improve the speed of 3D detection of high-temperature steel surface. In addition, surface defect detection based on DL

TABLE 3 Various classification algorithms

Type	Methods	Ref.	Advantages	Disadvantages
unsupervised	K-means	[135]	Be of simple principle, easy to realize, and highly interpretable model.	Needs to set the number of classes in advance.
	SOM	[33, 136]	Suitable for visualization of high-dimensional data, and can maintain the topological structure of input space.	When there are fewer input modes, the classification effect of the network depends on the order of input modes.
	Rough set	[12, 137]	Mathematical foundation is mature and does not require prior knowledge.	Decision rules are not very stable, which affects the classification accuracy.
	AutoEncoder	[138]	No need data annotation, and has strong generalization ability.	The output is degraded compared to its input.
	GAN	[139]	Uses back propagation and does not need Markov chain, and can generate clearer and authentic samples.	The training is unstable and not suitable for processing discrete data.
semi-supervised	CNN	[140, 141]	Only a small number of labeled samples and a large number of labeled samples are required.	Do not fully consider the uncertainty of the data distribution without class labels when there is noise.
	GAN	[142, 143]		
supervised	BP-NN	[30, 38, 55]	Has strong non-linear mapping ability, flexible network structure.	Slow training speed, and easy to fall into local minimum.
	LVQ	[124, 144]	Simple structure, powerful function and self adaptability.	The training process may not converge.
	CNN	[145–153]	Directly learn defect related features rather than hand-made features.	Need a large number of training samples.
	Bayesian classifiers	[161]	Be of intuitive and has strict mathematical proof.	Conditional probability density is generally difficult to determine
	KNN	[162–164]	Easy to understand and implement without estimating parameters.	The K value needs to be set in advance and cannot be adaptive
	SVM	[16, 18, 52, 76, 93, 113, 120] [121, 123, 124, 127, 128, 165–168]	With solid theoretical foundation for small samples, good robustness and strong generalization ability.	Be of time-consuming and usually requires more training samples
	AdaBoost	[22, 125]	Different classification algorithms can be cascaded as weak classifiers with high accuracy.	The number of weak classifiers is difficult to set, the training is time-consuming.
	Random forest	[94]	Has fast training speed, strong generalization, and is insensitive to the loss of some features.	Easy to fall into overfitting when the noise is large.
	Deep learning	[151–153]	Strong learning ability, good adaptability, and can automatically extract massive features.	Large amount of calculation, high requirements on hardware and large data set.

usually requires GPU to complete a huge amount of computation, such as in [145].

Embedded machine vision system usually integrates the functions of image acquisition and image processing. Using the powerful parallel computing ability of field programmable gate array (FPGA) and the advantages of digital signal process (DSP), the image acquisition and early image processing can be completed by DSP and FPGA to meet the requirements of real time. Zhao et al. [52] used high-speed optical fibre, high-speed FPGA and multi-core processor to realize online surface defect detection. Lai et al. [88] adopted DSP development board as a main processing component of real-time image processing system, which fulfilled threshold segmentation, morphological operations and edge detection algorithm.

Using lightweight network architecture or parallel processing in software can also improve the real-time performance of the system to a certain extent. Llenderrozos et al. [57] adopted parallel processing to make the efficiency of detection algorithm closely related to strip speed.

3) CNN is the most typical framework of DL in computer vision (CN) and has been widely used. In recent years, transformer model [174], originally used for natural language processing, has also been applied to CV and has been successfully applied to image classification [175] and object detection [176], which should soon be applied to steel surface defect detection.

4) At present, the theoretical research and practical application of surface defect detection based on machine vision have achieved gratifying results, but there are still the following main problems and difficulties.

1. Some factors such as illumination conditions, water vapour, dust and vibration will have adverse effects on image acquisition. Establishing a stable and reliable visual detection system to adapt to the interference of external adverse environment is the basic condition of detection.
2. There are many kinds and forms of steel surface defects; at the same time, it is difficult to determine the 'standard' type of defects and find the 'standard' image as a reference, which brings difficulties to defect detection. Most of the references listed here have no more than seven types of defects, and the types of defects need to be improved.
3. Steel surface defect detection has massive data, redundant information and high feature dimension. To extract defect information from massive data, the real-time performance of the algorithm is very important. Improving the accuracy, real time and robustness of the algorithm have always been the direction of efforts.
4. Relatively speaking, there are more off-line research than online detection in the literature. It is also ought to effort to carry out online detection rather than just off-line research. Based on academic research results, more online detection and mature industrial application are also aspects to be developed in the near future.
5. Due to the low signal-to-noise ratio (SNR) and complex optical imaging design of the detection system, there are few 3D detection of surface defects; few references integrate 2D and 3D information to classify steel surface defects. In addition, the research focus is shifting from traditional image processing and machine learning methods to DL methods.
6. With the development of computer technology, information technology and artificial intelligence, further research is needed to absorb the latest research results of biological vision and simulate the information processing function of human brain to build an intelligent machine vision system.

AUTHOR CONTRIBUTIONS

Bo Tang: writing, funding acquisition, project administration, supervision; Li Chen: formal analysis, investigation, suggestions for improvement; Wei Sun: investigation, polishing the article's language; Zhong-kang Lin: resources, collecting references and materials.

ACKNOWLEDGEMENT

This work was supported by the National Natural Science Foundation of China (No. 51874217).

CONFLICT OF INTEREST

The authors have declared no conflict of interest.

DATA AVAILABILITY STATEMENT

We certify that we have participated sufficiently in the work, but because this is a review, there is no data, model or code to be shared.

REFERENCES

1. Newman, T.S., Jain, A.K.: A survey of automated visual inspection. Comput. Vis. Image Underst. 61(2), 231–262 (1995)
2. Xie, X.: A review of recent advances in surface defect detection using texture analysis techniques. Elcvia Electron. Lett. on CV & IA 7(3), 1–22 (2008)
3. Czimmermann, T., Ciuti, G., Milazzo, M., Chiurazzi, M., Roccella, S., Oddo, C.M., Dario, P.: Visual-based defect detection and classification approaches for industrial applications – a survey. Sensors 20(5), 1–25 (2020)
4. Li, W., Lu, C., Zhang, J.: Review of vision real-time inspection algorithm for rolling steel surface defects. Adv. Mat. Res. 308-310, 1328–1332 (2011)
5. Neogi, N., Mohanta, D.K., Dutta, P.K.: Review of vision-based steel surface inspection systems. EURASIP J. Image Video. Process. (1), 1–19 (2014)
6. Sun, X., Gu, J., Tang, S., et al.: Research progress of visual inspection technology of steel products – a review. Appl. Sci. 8, 2195, (2018)
7. Luo, Q., Fang, X., Liu, L., et al.: Automated visual defect detection for flat steel surface: a survey. IEEE Trans. Instrum. Meas. 69(3), 626–644 (2020)
8. Luo, Q., Fang, X., Su, J., et al. Automated visual defect classification for flat steel surface: a survey. IEEE Trans. Instrum. Meas. 69(12), 9329–9349 (2020)
9. Song, K., Hu, S., Yan, Y.: Automatic recognition of surface defects on hot-rolled steel strip using scattering convolution network. J. Comput. Inf. Syst. (2014), 10(7) 3049–3055
10. Amin, D., Akhter, S.: Deep learning-based defect detection system in steel sheet surfaces. In: 2020 IEEE Region 10 Symposium (TENSYMP), pp. 444–448. IEEE, Piscataway, NJ (2020)
11. Li, Q.Y., Ren, S.W.: A real-time visual inspection system for discrete surface defects of rail heads. IEEE Trans. Instrum. Meas. 61(8), 2189–2199 (2012)
12. Zhao, L., Zhang, Y., Xu, X., et al.: Defect inspection in hot slab surface: multi-source CCD imaging based fuzzy-rough sets method. In: Conference on Applications of Digital Image Processing, pp. 9971B.1–7, SPIE. Bellingham, WA (2016)
13. Peng, T., He, Y., Li, B., et al.: Research and development of tin steel strip surface online inspection system based on TDI imaging technology. Infrared Laser Eng. 43(1), 294–299 (2014). (Chinese)
14. Yun, J.P., Kim, D., Kim, K., et al.: Vision-based surface defect inspection for thick steel plates. Opt. Eng. 56(5), 053108–1–053108–12 (2017)
15. Wu, G., Hwak, H., Jang, S., et al.: Design of online surface inspection system of hot rolled strips. In: IEEE International Conference on Automation and Logistics, pp. 2291–2295. IEEE, Piscataway, NJ (2008)
16. Yun, J.P., Choi, D.C., Jeon, Y.J., et al.: Defect inspection system for steel wire rods produced by hot rolling process. Int. J. Adv. Manuf. Technol. 70(9-12), 1625–1634 (2014)
17. Pernkopf, F., O'Leary, P.: Image acquisition techniques for automatic visual inspection of metallic surfaces. NDT Int. 36(8), 609–617 (2013)
18. Xu, H., Zhi, Y., Yu, S.: On study of a method for detecting micro-deformation defects of steel plate surface. In: AOPC 2020: Optics Ultra

Precision Manufacturing and Testing: On study of a method for detecting micro-deformation defects of steel plate surface, 115680 M.1-10. SPIE, Bellingham, WA (2020)
19. Wei, Y., Yan, Y., Li, B., et al. Development of a surface defect inspection system for cold rolled strip based on bright-dark filed mode. Adv. Mat. Res. 118-120, 762–7662 (2010)
20. Juan, M.C., José, F.S., Francisco, M.: A comparative study of image processing thresholding algorithms on residual oxide scale detection in stainless steel production lines. Procedia Manuf. 41, 216–223 (2019)
21. Ou, Y., Zhang, L., Zhao, L., et al.: Experimental study on quantitative surface defect depth detection based on laser scanning technology in continuous casting. Ironmak. Steelmak. 38(5), 363–368 (2011)
22. Xu, K., Yang, C.L., Zhou, P., et al.: On-line detection technique of surface cracks for continuous casting billets based on linear lasers. J. Univer. Sci. Technol. Beijing. 31(12), 1620–1624 (2009). (Chinese)
23. Xu, K., Yang, C., Zhou, P., et al.: 3D detection technique of surface defects for steel bar based on laser linear lasers. J. Mech. Eng. 46(8), 1–5 (2010). (Chinese)
24. Zhang, X.L., Ouyang, Q., Peng, S., et al.: Continuous casting slab surface crack depth measurement using sinusoidal phase grating method. Ironmak. Steelmak. 41(5), 387–393 (2014)
25. Wen, X., Song, K., Niu, M., et al.: A three-dimensional inspection system for high temperature steel product surface sample height using stereo vision and blue encoded patterns. Optik. 130, 131–148 (2017)
26. Pindor, L., Hefnr, S., Cibylka, J., et al.: Non-destructive testing of continuously cast billets by means of the laser triangulation method. In: Proceedings of 18th World Conference on Non-destructive Testing, pp. 1759–1766. Curran Associates, Inc., New York (2012)
27. Miyamoto, R., Mizutani, K., Wakatsuki, N., Ebihara, T.: Defect detection in billet using plane-wave and time-of-flight deviation with transmission method. In: 2018 IEEE International Ultrasonics Symposium (IUS), pp. 23–26. IEEE, Piscataway, NJ (2018)
28. Kang, D., Yu, J., Won, S.: Development of an inspection system for planar steel surface using multispectral photometric stereo. Opt. Eng. 52(3), 254–260 (2013)
29. Xu, K., Gan, W., Jio, J., et al.: 3D reconstruction of steel rail surface based on photometric stereo. Hebei Metall. 305(5), 18–22, (2021). (Chinese)
30. Shi, T., Kong, J., Wang, X., et al.: Improved Sobel algorithm for defect detection of rail surfaces with enhanced efficiency and accuracy. J. Cent. South Univ. 23(11), 2867–2875 (2016)
31. Xia, C., Li, H., Zhang, J., et al.: Gaussian filtering algorithm describing the topography of temper rolled strip and related edge effect. Mater./Mater. Test. 60(1), 61–67 (2017)
32. Choi, S.H., Yun, J.P., Seo, B., et al.: Real-time defects detection algorithm for high-speed steel bar in coil. Enformatika, 21, 66–70 (2007)
33. Martins, L.A.O., Padua, F.L.C., Almeida, P.E.M.: Automatic detection of surface defects on rolled steel using computer vision and artificial neural networks. In: Proc. 36th Annu. Conf. IEEE Ind. Electron. pp. 1081–1086. IEEE, Piscataway, NJ (2010)
34. Xue, B., Wu, Z.: Key technologies of steel plate surface defect detection system based on artificial intelligence machine vision. Wirel. Commun. Mob. Comput. 6, 1–12 (2021)
35. Gong, R., Chu, M., Wang, A., et al.: A fast detection method for region of defect on strip steel surface. ISIJ Int. 55(1), 207–212 (2015)
36. Li, W., Lu, C., Zhang, J.: A local annular contrast based real-time inspection algorithm for steel bar surface defects. Appl. Surf. Sci. 258(16) 6080–6086, (2012)
37. Ye, G., Li, Y., Ma, Z., et al.: End-to-end aluminum strip surface defects detection and recognition method based on ViBe. J. Zhejiang Univ. Sci. 54(10), 1906–1914 (2020). (Chinese)
38. Yang, C., Zhang, J., Ji, G., et al.: Recognition of defects in steel surface image based on neural networks and morphology. In: Second Workshop on Digital Media and its Application in Museum & Heritages (DMAMH 2007), pp. 72–77. IEEE Computer Society, Los Alamitos (2007)
39. Shi, K., Wei, W.: Image denoising method of surface defect on cold rolled aluminum sheet by bilateral filtering. Surf. Technol. 47(09), 326–332 (2018). (Chinese)
40. Blackledge, J., Dubovitskiy, D.: A surface inspection machine vision system that includes fractal texture analysis. J. Intell. Syst. 3(2), 76–89 (2008)
41. Yun, J.P., Jeon, Y.J., Choi, D.C., et al.: Real-time defect detection of steel wire rods using wavelet filters optimized by univariate dynamic encoding algorithm for searches. J. Opt. Soc Am. A 29(5), 797–807 (2012)
42. Chen, Z., Wang, P., Xie, S.: Image enhancement method for steel surface defects based on DT-CWT. Appl. Mech. Mater. 380-384, 3686–3689 (2013)
43. Liu, W., Yan, Y.: Automated surface defect detection for cold-rolled steel strip based on wavelet anisotropic diffusion method. Int. J. Ind. Syst. Eng. 17(2), 224–239 (2014)
44. Le Pennec, E., Mallat, S.: Sparse geometric image representations with bandelets. IEEE Trans. Image Process. 14(4), 423–438 (2005)
45. Candes, E.J., Donoho, D.L.: Curvelets – a surprisingly effective no adaptive representation for objects with edges. In: Cohen, A., Rabut, C., Schumaker, L. (eds.) Curve & Surface Fitting, pp. 105–120. Vanderbilt University Press, Nashville, TN (2000)
46. Do, M.N., Vetterli, M.: The contourlet transform: an efficient directional multi resolution image representation. IEEE Trans. Image Process. 14(12), 2091–2106 (2005)
47. Krommweh, J.: Tetrolet transform: A new adaptive Haar wavelet algorithm for sparse image representation. J. Vis. Commun. Image Represent. 21(4), 364–374 (2010)
48. Zhang, H., Jin, X., Jonathan Wu, Q.M., et al.: Automatic visual detection system of railway surface defects with curvature filter and improved Gaussian mixture model. IEEE Trans. Instrum. Meas. 67(7), 1593–1608 (2018)
49. Li, C., Zang, X., Cheng, W., et al.: Image denoising method on surface of steel strip based on partial differential equations. J. Dalian Maritime Univ. 34(1), 71–74 (2008). (Chinese)
50. Vorobel, R., Ivasenko, I., Berehulyak, O., et al.: Segmentation of rust defects on painted steel surfaces by intelligent image analysis. Autom. Constr. 123, 103515 (2021)
51. Nand, G.K., Neogi, N.: Defect detection of steel surface using entropy segmentation. In: 2014 Annual IEEE India Conference (INDICON), pp. 1–6. IEEE, Piscataway, NJ (2014)
52. Zhao, J., Yang, Y., Li, G.: The cold rolling strip surface defect on-line inspection system based on machine vision. In: 2010 Second Pacific-Asia Conference on Circuits, Communications and System, pp. 402–405. IEEE, Piscataway, NJ (2010)
53. Tang, B., Kong, J., Wang, X., et al.: Image enhancement and segmentation algorithm for low contrast micro defects on steel plate. J. Image Graph. 25(1), 81–91, (2020). (Chinese)
54. Zhang, B., Liu, X., Wu, S.: IPSO based binarization processing in uneven illumination images for billet defect detection. In: Proceedings of the 13th IEEE Conference on Industrial Electronics and Applications (ICIEA), pp. 1923–1928. IEEE, Piscataway, NJ (2018)
55. Yazdchi, M.R., Mahyari, A.G., Nazeri, A.: Detection and classification of surface defects of cold rolling mill steel using morphology and neural network. In: 2008 International Conference on Computational Intelligence for Modelling Control & Automation, pp. 1071–1076. IEEE, Piscataway, NJ (2008)
56. Wang, H., Zhu, D.: Tang wei: an algorithm of strip surface defect detection based on grayscale projection. J. Northeast. Univ. Natur. Sci. 29(3), 375–377 (2008). (Chinese)
57. LIenderrozos, R.G., Garcia, I.A., Enguita Gonzalez, J.M., et al.: Automatic area based registration method and its application to the surface inspection of steel industry products. In: Conference on Automated Visual inspection pp. 87911I.1–87911I.15. SPIE, Bellingham, WA (2013)
58. Hsu, C.Y., Kang, L.W., Lin, C.Y., et al.: Multiple image features: vision-based detection of steel billet surface defects via fusion of multiple image features. Front. Artif. Intell. Appl. 274, 1239–1247 (2015)
59. Liu, H.W., Lan, Y.Y., Lee, H.W., et al.: Steel surface in-line inspection using machine vision. In: First International Workshop on Pattern Recognition, pp. 100110X–100110X–5, SPIE. Bellingham, WA (2016)

60. Neogi, N., Mohanta, D.K., Dutta, P.K.: Defect detection of steel surfaces with global adaptive percentile thresholding of gradient image. J. Inst. Eng. 98(6), 557–565 (2017)
61. Jianzhuang, L., Wenqing, L.: The automatic thresholding of gray-level pictures via two-dimensional OTSU method. Acta Autom. Sin. 19(1), 101–105 (1993). (Chinese)
62. MA, J.K., Hua, C.J., Zhou, H.Y.: Cold rolling thin strip defects segmentation based on threshold decomposition. In: 2018 37th Chinese Control Conference (CCC), pp. 9186–919. IEEE, Piscataway, NJ (2018)
63. Kapur, J.N., Sahoo, P.K., Wong, A.K.C.: A new method of gray level picture thresholding using the entropy of the histogram. Comput. Vis. Graph. Image Process. 29(2), 273–285 (1985)
64. Yen, J.C., Chang, F.J., Chang, S.: A new criterion for automatic multilevel thresholding. IEEE Trans. Image Process. 6(3), 370–377 (1995)
65. Sharifzadeh, M., Alirezaee, S., Amirfattahi, R., Sadri, S.: Detection of steel defect using the image processing algorithms. In: 2008 IEEE International Multitopic Conference, pp. 125–127. IEEE, Piscataway, NJ (2008)
66. Canny, J.: A computational approach to edge detection. IEEE Trans. Pattern Anal. Mach. Intell. 8(6), 679–698 (1986)
67. Tang, B., Kong, J., Wang, X., Chen, L.: Surface inspection system of steel strip based on machine vision. In: 2009 First International Workshop on Database Technology and Applications, pp. 359–362. IEEE, Piscataway, NJ (2009)
68. Yun, J.P., Choi, S.H., Seo, B., et al.: Real-time vision-based defect inspection for high-speed steel products. Opt. Eng. 47(7), 685–694 (2008)
69. Bhattacharya, A.K., Tiwari, A., Aditya, D., et al.: Online evaluation of steel slab quality in production phase by surface crack image segmentation using relative fuzzy connectedness. In: Proceedings of the 2007 International Conference on Image Processing, Computer Vision, and Pattern Recognition (IPCV 2007), pp. 353–359. CSREA Press (2007)
70. Li, Q., Jin, J.H., Chang, T.S.: Detection and diagnosis of repetitive surface defects for hot rolling processes. In: *Transactions of the North American Manufacturing Research Institution of SME* pp. 615–622. Detection and diagnosis of repetitive surface defects for hot rolling processes, Dearborn, MI (2010)
71. Li, L., Hao, P.: Steel plate corrugation defect intelligent detection method based on picture cropping and region growing algorithm. In: 14th IEEE Conference on Industrial Electronics and Applications (ICIEA), pp. 587–590. IEEE, Piscataway, NJ (2019)
72. Xu, S., Guan, S., Chen, L.: Steel strip defect detection based on human visual attention mechanism model. App. Mech. Mater. 530–531, 456–462, (2014)
73. Zhao, C., Zhu, H., Jing, W.: Steel plate surface defect recognition method based on depth information. In: 2019 IEEE 8th Data Driven Control and Learning System Conference, pp. 322–327. IEEE, Piscataway, NJ (2019)
74. Chen, Y., Zhan, J., Zhang, H.: Segmentation algorithm of armor plate surface images based on improved visual attention mechanism. Open Cybern. Syst. J. 9(1), 1385–1392, (2015)
75. Jaffery, Z.A., Ahmad, N., Sharma, D.: Performance comparison of segmentation techniques for detection of defect in rail head surface images. In: 2017 International Conference on Multimedia, Signal Processing and Communication Technologies (IMPACT), pp. 132–136. IEEE, Piscataway, NJ (2017)
76. Chu, M., Liu, X., Gong, R., et al.: Multi-class classification method using twin support vector machines with multi-information for steel surface defects. Chemom. Intell. Lab. Syst. 176, 108–118 (2018)
77. Yang, S., He, Y., Zhao, W., et al.: Application of the Mean shift algorithm in steel strip image segmentation. J. Xidian Univ. 34(6), 1015–1018, (2007)
78. Saeedi, J., Dotta, M., Galli, A., et al.: Measurement and inspection of electrical discharge machined steel surfaces using deep neural networks. Mach. Vis. Appl. 32(21), 20–35 (2021)
79. Chaudhari, C.V., Gupta, R.K., S, A.: Feagade: A novel approach of crack detection in railway track using fuzzy c means and level set method. In: 2nd International Conference on Data, Engineering and Applications (IDEA), pp. 1–7. IEEE, Piscataway, NJ (2020)
80. Holland, J.: Adaptation in Natural and Artificial Systems [M]. University of Michgan Press, Ann Arbor, MI (1975)
81. Ryu, S.G., Koo, G., Kim, S.W.: An adaptive selection of filter parameters: defect detection in steel image using wavelet reconstruction method. ISIJ Int. 60(8), 1703–1713, (2020)
82. Jeon, Y., Yun, J.P., Choi, D., Kim, S.W.: Defect detection algorithm for corner cracks in steel billet using discrete wavelet transform. In: 2009 ICCAS-SICE, Fukuoka, pp. 2602–2606. IEEE, Piscataway, NJ (2009)
83. Zhang, J., Kang, D., Won, S.: Detection of scratch defects for wire rod in steelmaking process. In: ICCAS 2010, Gyeonggi-do, Korea (South), pp. 319–323 (2010)
84. Chen, H., Xu, S., Liu, K., et al.: Strip defect detection based on Gabor wavelet and weighted Mahalanobis distance. Journal of Electronic Measurement and Instrument. 30(5), 786–793, (2016). (Chinese)
85. Song, K., Hu, S., Yan, Y., et al.: Surface defect detection method using saliency linear scanning morphology for silicon steel strip under oil pollution interference. ISIJ Int. 54(11), 2598–2607 (2014)
86. Zeiler, A., Steinboeck, A., Vincze, M., et al.: Vision-based inspection and segmentation of trimmed steel edges. IFAC-PapersOnLine. 52(14), 165–170, (2019)
87. Lu, J., Wu, G., Zuo, Y., et al.: Research on the segmentation method of surface defects of galvanised sheet under complex texture background. The Journal of Engineering. 14, 9059–9063, (2019)
88. Lai, K., Zhang, H., Dai, D., et al.: New approach to classification of surface defects in steel plate based on fuzzy neural network. In: Proceedings of SPIE Conference on Optical Information Processing Technology, 447–456. SPIE, Bellingham, WA (2020)
89. Tang, B., Kong, J., Wang, X., et al.: Steel strip surface defects detection based on mathematical morphology. Journal of Iron and Steel Research. 22(10), 56–59, (2010). (Chinese)
90. Liu, M., Liu, Y., Hu, H., et al.: Genetic algorithm and mathematical morphology based binarization method for strip steel defect image with non-uniform illumination. J. Vis. Commun. Image Represent. 37, 70–77 (2016)
91. Xu, K., Song, M., Yang, C., et al.: Application of hidden Markov tree model to on-line detection of surface defects for steel strips. Jixie Gongcheng Xuebao. 49(22), 34–40, (2013)
92. Guo, Y., Sun, Z., Sun, H., et al.: Texture feature extraction of steel strip surface defect based on gray level co-occurrence matrix. In: International Conference on Machine Learning and Cybernetics, pp. 217–221. IEEE, Piscataway, NJ (2015)
93. Chu, M., Wang, A., Gong, R., et al.: Strip steel surface defect recognition based on novel feature extraction and enhanced least squares twin support vector machine. ISIJ Int. 54(7), 1638–1645 (2014)
94. Wang, Y., Xia, H., Yuan, X., et al.: Distributed defect recognition on steel surfaces using an improved random forest algorithm with optimal multi-feature-set fusion. Multimedia Tools and Applications. 77(13), 16741–16770, (2018)
95. Luo, Q., Fang, X., Sun, Y., et al.: Surface defect classification for hot-rolled steel strips by selectively dominant local binary patterns. IEEE Access 7, 23488–23499, (2019)
96. Samsudin, S.S., Arof, H., Harun, S.W., et al.: Steel surface defect classification using multi-resolution empirical mode decomposition and LBP. Meas. Sci. Technol. 32, art. no. 015601, (2021)
97. Liu, Y., Jin, Y., Ma, H.: Surface defect classification of steels based on ensemble of extreme learning machines. In: 2019 WRC Symposium on Advanced Robotics and Automation (WRC SARA), pp. 203–208. IEEE, Piscataway, NJ (2019)
98. Mansano, M., Pavesi, L., Oliveira, L.S., Britto, A., Koerich, A.: Inspection of metallic surfaces using local binary patterns. In: IECON 2011 – 37th Annual Conference of the IEEE Industrial Electronics Society, pp. 2227–2231. IEEE, Piscataway, NJ (2011)
99. Guo, Z., Zhang, L., Zhang, D.: A completed modeling of local binary pattern operator for texture classification. IEEE Trans. Image Process. 19(6), 1657–1663 (2010)
100. Song, K., Yan, Y.: A noise robust method based on completed local binary patterns for hot-rolled steel strip surface defects. Appl. Surf. Sci. 285(21), 858–864, (2013)

101. Chu, M.X., Gong, R.F.: Invariant feature extraction method based on smoothed local binary pattern for strip steel surface defect. ISIJ Int. vol. 55(9), 1956–1962, (2015)
102. Luo, Q., Sun, Y., Li, P., et al: Generalized completed local binary patterns for time efficient steel surface defect classification. IEEE Trans. Instrum. Meas. 68(3), 667–679, (2019)
103. Samadani, M.: Detection and classification of surface defects of cold rolling mill steel using image processing and neural network. Majlesi Journal of Multimedia Processing. 1071–1096 (2012)
104. Xu, K., Zhou, P., Yang, C.: Application of fractal dimension feature to recognition of surface defects on hot-rolled strips. App. Mech. Mater. 152-154, 526–530, (2012)
105. Yazdchi, M., Yazdi, M., Mahyari, A.G.: Steel surface defect detection using texture segmentation based on multifractal dimension. In: 2009 International Conference on Digital Image Processing, pp. 346–350. IEEE, Piscataway, NJC (2009)
106. Xu, K., Li, W., Yang, C.: Feature extraction based on amplitude spectrum and moment invariants and its application. Acta Autom. Sin. 32(3), 470–474 (2006). (Chinese)
107. Cong, J., Yan, Y., Dong, D.: Application of Gabor filter to strip surface defect detection. Transactions of the China Welding Institution. 31(2), 257–260, (2010). (Chinese)
108. Wu, J., Xu, K., Xu, J.,et al.: Recognition method of surface defects based on Gabor wavelet and kernel locality preserving projections. Acta Autom. Sin. 36(3), 438–441 (2010). (Chinese)
109. Yun, J.P., Choi, S.H., Seo, B., et al.: Defects detection of billet surface using optimized Gabor filters. 17th *IFAC World Congress*, pp. 77–82. Curran Associates, Inc., NY (2008)
110. Lee, C.S., Choi, C.-H., Choi, J.Y., et al.: Feature extraction algorithm based on adaptive wavelet packet for surface defect classification. In: Proceedings of 3rd IEEE International Conference on Image Processing, pp. 673–676. IEL, USA (1996)
111. Zhang, J., Yang, Y.: Icccas: A method of pattern identification and classification for cold rolling steel strip based on biorthogonal wavelet neural network. In: 2007 International Conference on Communications, Circuits and Systems, pp. 976–979. IEEE, Piscataway, NJ (2007)
112. Ghorai, S., Mukherjee, A., Gangadaran, M., et al.: Automatic defect detection on hot-rolled flat steel products. IEEE Trans. Instrum. Meas. 62(3), 612–621, (2013)
113. Xu, K., Wang, L., Wang, J.: Surface defect recognition of hot-rolled steel plates based on Tetrolet transform. J. Mech. Eng. 52(4), 13–19 (2016). (Chinese)
114. Xu, K., Liu, S., Ai, Y.: Application of Shearlet transform to classification of surface defects for metals. Image and Vision Computing. 35, 23–30 (2015)
115. Xu, K., Xu, Y., Zhou, P., et al: Application of RNAMlet to surface defect identification of steels. Optics and Lasers in Engineering. 105, 110–117 (2018)
116. Hu, M.K.: Visual pattern recognition by moment invariants. IRE Transactions on Information Theory. 8(2), 179–187, (1962)
117. Gao, Y., Yang, Y.: Classification based on multi-classifier of SVM fusion for steel strip surface defects. In: 32nd Chinese Control Conference , pp. 3617–3622. IEEE, Piscataway, NJ (2013)
118. Zhou, P., Xu, K., Yang, C.: Surface defect recognition for moderately thick plates based on a SIFT operator. Journal of Tsinghua University (Science and Technology). 58(10), 881–887 (2018). (Chinese)
119. Suvdaa, B., Ahn, J., Ko, J.: Steel surface defects detection and classification using SIFT and voting strategy. International Journal of Software Engineering and Its Applications. 6(2), 161–165 (2012)
120. Hu, H., Liu, Y., Liu, M., et al.: Surface defect classification in large-scale strip steel image collection via hybrid chromosome genetic algorithm. Neurocomputing. 181, 86–95 (2016)
121. Hu, H., Li, Y., Liu, M., Liang, W.: Classification of defects in steel strip surface based on multiclass support vector machine. Multimedia Tools Appl., 69(1), 199–216, (2014)
122. Tolba, A.S., Khan, H.A., Raafat, H.M.: Automated visual inspection of flat surface products using feature fusion. In: 2009 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT), pp. 160–165. IEEE, Piscataway, NJ (2009)
123. Choi, K., Koo, K., Lee, J.S.: Development of defect classification algorithm for Posco rolling strip surface inspection system. In: 2006 SICE-ICASE International Joint Conference, pp. 2499–2502. IEEE, Piscataway, NJ (2006)
124. Chen, Y., Chen, L., Liu, X., et al.: Real-time steel inspection system based on support vector machine and multiple kernel learning. Practical Applications of Intelligent Systems. 124, 185–190 (2011)
125. Hu, L., Zhou, M., Xiang, F., et al.: Modeling and recognition of steel-plate surface defects based on a new backward boosting algorithm. The International Journal of Advanced Manufacturing Technology. 94(9-12), 4317–4328 (2017)
126. Zhang, Z.F., Liu, W., Ostrosi, E., et al.: Steel strip surface inspection through the combination of feature selection and multiclass classifiers. Engineering Computations. 38(4), 1831–1850 (2020)
127. Gong, R., Wu, C., Chu, M., et al: The strip steel surface defect recognition based on multiple support vector hyper-sphere with feature and sample weights. Steel Res. Int. 87(12), 1678–1685 (2016)
128. Zaghdoudi, R., Seridi, H., Boudiaf, A., et al.: Binary Gabor pattern (BGP) descriptor and principal component analysis (PCA) for steel surface defects classification. In: 2020 International Conference on Advanced Aspects of Software Engineering (ICAASE), pp. 1–7. IEEE, Piscataway, NJ (2020)
129. Miao, F., Tian, Y.: c. In: 39th Chinese Control Conference (CCC), pp. 6562–6565. IEEE, Piscataway, NJ (2020)
130. Tang, B., Kong, J., Wang, X., et al.: Feature dimensions reduction and its optimization for steel strip surface defect based on genetic algorithm. Journal of Iron and Steel Research. 23(9), 59–62 (2011). (Chinese)
131. Ai, Y., Xu, K.: Feature extraction based on contourlet transform and its application to surface inspection of metals. Optical Engineering. 51(11), 113605, (2012)
132. Xu, K., Ai, Y., Wu, X.: Application of multi-scale feature extraction to surface defect classification of hot-rolled steels. International Journal of Minerals, Metallurgy and Materials. 20(1), 37–41, (2013)
133. Cord, A., Bach, F., Jeulin, D.: Texture classification by statistical learning from morphological image processing: application to metallic surfaces. Journal of Microscopy. 239(2), 159–166, (2010)
134. He, D., Xu, K., Wang, D.: Design of multi-scale receptive field convolutional neural network for surface inspection of hot rolled steels. Image and Vision Computing. 89, 12–20 (2019)
135. Cohn, R., Holm, E.: Unsupervised machine learning via transfer learning and k-means clustering to classify materials image data. Integrating Materials and Manufacturing Innovation. 10(2), 231–244 (2020)
136. Wang, Y., Yan, Y., Wu, Y.: Winner trace marking in self-organizing neural network for classification. In: 2008 International Symposium on Computer Science and Computational Technology, pp. 255–260. IEEE Computer Society, LA (2008)
137. Tang, B., Kong, J., Wang, X., et al.: Research on steel strip surface defect images classification based on rough set theory. J. Image Graph. 16(17), 1213–1218 (2011). (Chinese)
138. Lv, Q., He, Y.: Song: Improved sacked denoising autoencoders-based defect detection in bar surface. In: Chinese Automation Congress (CAC), pp. 675–680. IEEE, Piscataway, NJ (2018)
139. Liu, K., Li, A., Wen, X., et al.: Steel surface defect detection using GAN and one-class classifier. In: 25th International Conference on Automation and Computing (ICAC), pp. 59–5600. IEEE, Piscataway, NJ (2019)
140. Gao, Y., Gao, L., Li, X., et al.: A semi-supervised convolutional neural network-based method for steel surface defect recognition. Robotics and Computer Integrated Manufacturing. 61, art. no. 101825, (2020)
141. Zheng, X., Wang, H., Chen, J., et al.: A generic semi-supervised deep learning-based approach for automated surface inspection. IEEE Access 8, 114088–114099, (2020)
142. He, Y., Song, K., Dong, H., et al.: Semi-supervised defect classification of steel surface based on multi-training and generative adversarial network. Optics and Lasers in Engineering. 122, 294–302, (2019)

143. He, D., Xu, K., Zhou, P., et al.: Surface defect classification of steels with a new semi-supervised learning method. Optics and Lasers in Engineering. 117, 40–48, (2019)
144. Han, Y., Hong, Y.: Research on defect surface online detection, classification and recognition algorithm for strip steel. Journal of Optoelectronics·Laser. 26(2), 320–327, (2015). (Chinese)
145. Yi, L., Li, G., Jiang, M.: An end-to-end steel strip surface defects recognition system based on convolutional neural networks. Steel Res. Int. 88(2), 176–187 (2017)
146. Huang, Z., Wu, J., Xie, F.: Automatic recognition of surface defects for hot-rolled steel strip based on deep attention residual convolutional neural network. Mater. Lett. 293, 129707, (2021)
147. Kim, M.S., Park, T., Park, P.: Classification of steel surface defect using convolutional neural network with few images. In: 12th Asian Control Conference (ASCC), pp. 1398–1401. IEEE, Piscataway, NJ (2019)
148. Ren, S., He, K., Girshick, R., et al. Faster R-CNN: towards real-time object detection with region proposal networks. IEEE Trans. Pattern Anal. Mach. Intell. 39(6), 1137–1149 (2017)
149. Liu, W., Anguelov, D., Erhan, et al.: SSD: Single shot multibox detector. In: European Conference on Computer Vision, pp. 21–37. Springer, Berlin (2016)
150. Redmon, J., Divvala, S., Girshick, R., et al.: You only look once: unified, real-time object detection. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2016), pp. 779–788. IEEE, Piscataway, NJ (2016)
151. Wei, R., Song, Y., Zhang, Y.: Enhanced faster region convolutional neural networks for steel surface defect detection. ISIJ Int. 60(3), 539–545 (2020)
152. Lin, C.-Y., Chen, C.-H., Yang, C.-Y., et al.: Cascading convolutional neural network for steel surface defect detection. Advances in Intelligent Systems and Computing. 965, 202–212 (2020)
153. Li, J., Su, Z., Geng, J., et al.: Real-time detection of steel strip surface defects based on improved YOLO detection network. IFAC-PapersOnLine. 51(21), 76–81, (2018)
154. Shelhamer, E., Long, J., T. Darrell: Fully convolutional networks for semantic segmentation. IEEE Trans. Pattern Anal. Mach. Intell. 39(4), 640–651 (2017)
155. Girshick, R., Donahue, J., Darrell, T., Malik, J.: Rich feature hierarchies for accurate object detection and semantic segmentation. In: 2014 IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2014), pp. 580–587. IEEE, Piscataway, NJ (2014)
156. Xian, T., Zhang, D., Ma, W., et al.: Automatic metallic surface defect detection and recognition with convolutional neural networks. Appl. Sci. 8, 1575, (2018)
157. Zhang, G., Pan, Y., Zhang, L.: Semi-supervised learning with GAN for automatic defect detection from images. Autom. Constr. 128, art. no. 103764, (2021)
158. Huang, Z., Wu, J., Xie, F.: Automatic surface defect segmentation for hot-rolled steel strip using depth-wise separable U-shape network. Mater. Lett. 301, art. no. 130271, (2021)
159. Chen, K., Zeng, Z., Yang, J.: A deep region-based pyramid neural network for automatic detection and multi-classification of various surface defects of aluminum alloys. Journal of Building Engineering. 43, art. no. 102523, (2021)
160. He, Y., Song, K., Meng, Q., Yan, Y.: An end-to-end steel surface defect detection approach via fusing multiple hierarchical features. IEEE Trans. Instrum. Meas. 69(4), 1493–1504, (2020)
161. Pernkopf, F.: Detection of surface defects on raw steel blocks using Bayesian network classifiers. Pattern Analysis and Applications. 7(1), 333–342, (2004)
162. Mandriota, C., Nitti, M., Ancona, N., et al.: Filter-based feature selection for rail defect detection. Machine Vision & Applications. 15(4), 179–185, (2004)
163. Wiltschi, K., Pinz, A.: Lindeberg: an automatic assessment scheme for steel quality inspection. Mach. Vis. Appl. 12(13), 113–128, (2000)
164. Mentouri, Z., Moussaoui, A., Boudjehem, D., et al.: Steel strip surface defect identification based on binarized statistical features. UPB Scientific Bulletin, Series B: Chemistry and Materials Science. 84(4), 145–156, (2018)
165. Jayadeva, R.K., Chandra, S.: Twin support vector machines for pattern classification. IEEE Trans. Pattern Anal. Mach. Intell. 29(5), 905–910 (2007)
166. Suykens, J.: Vandewalle: least squares support vector machine classifiers. Neural Processing Letters. 9(3), 293–300, (1999)
167. Lin, C., Wang, S.: Fuzzy support vector machines. IEEE Transactions on Neural Networks. 13(2), 464–471, (2002)
168. Agarwal, K., Shivpuri, R., Zhu, Y., et al.: Process knowledge based multi-class support vector classification (PK-MSVM) approach for surface defects in hot rolling. Expert Systems with Applications. 38(6), 7251–7262, (2011)
169. Tao, X., Hou, W., Xu, D.: A survey of surface defect detection methods based on deep learning. Acta Autom. Sin. 47(5), 1017–1034 (2021). (Chinese)
170. Wei, T., Cao, D., Zheng, C., et al.: A simulation-based few samples learning method for surface defect segmentation. Neurocomputing. 412(6), 461–476, (2020)
171. Jain, S., Seth, G., Paruthi, A., et al.: Synthetic data augmentation for surface defect detection and classification using deep learning. Journal of Intelligent Manufacturing. 33(4), 1007–1020 (2020)
172. Deshpande, A.M., Minai, A.A., Kumar, M.: One-shot recognition of manufacturing defects in steel surfaces. Procedia Manuf. 48, 1064–1071, (2020)
173. Zhang, S., Zhang, Q., Gu, J., et al.: Visual inspection of steel surface defects based on domain adaptation and adaptive convolutional neural network. Mechanical Systems and Signal Processing. 153, art. no. 107541, (2021)
174. Vaswani, A., Shazeer, N., Parmar, N., et al.: Attention is all you need. Advances in Neural Information Processing Systems. vol 30, 5998–6008, (2017)
175. Dosovitskiy, A., Beyer, L., Kolesnikov, A., et al.: An image is worth 16×16 words: Transformers for Image Recognition at Scale. 2021 International Conference on Learning Representations (ICLR 2021), (2021)
176. Carion, N., Massa, F., Synnaeve, G., et al.: End-to-end object detection with transformers. In: 2020 European Conference on Computer Vision (ECCV 2020), pp. 213–229. Springer, Cham (2020)

How to cite this article: Tang, B., Chen, L., Sun, W., Lin, Z.: Review of surface defect detection of steel products based on machine vision. IET Image Process. 17, 303–322 (2023). https://doi.org/10.1049/ipr2.12647