



A Review of Research on Detection and Evaluation of Rail Surface Defects

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A Review of Research on Detection and Evaluation of the Rail Surface Defects

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Abstract: Defects on the rail surface will hasten the wear of the wheels. At the same time, when the wheel is periodically hitting and rolling surface defected, the defects will gradually develop into the interior, which significantly increases the possibility of a train derailment and serious safety accidents. A timely checking of the railway tracks to find defects as early as possible is a basic condition for ensuring the safety of railway operations. It also prolongs the service life of railways because most of the rolling contact fatigue (RCF) can be eliminated during rail grinding. Such defects appear as spalling and cracks in the first stage of the rail surface. Manual detection has been challenging to meet the large-scale railway running mileage. Therefore, a more efficient automatic detection method is indispensable. This article reviews the latest research and exploration on the defect inspection of rail surfaces in recent years. In the article, not only the application of traditional ultrasonic and acceleration detection methods but also contributing computer vision and deep learning to detect defects on the rail surface. The new detection technology can even classify and evaluate the damage, further improving the efficiency of the detection system. Besides, the emerging research on defect state prediction to reduce inspection costs is interesting.

Keywords: rail surface defects; machine learning; detect; CNN

1 Introduction

In the 21st century, railway transport will be an increasingly important task related to the developed world and society. It started in the 19th and 20th centuries with enormous railway construction procedures worldwide [1–3]. Railway construction investment has been continually increasing. It can be said that traffic safety is an important consideration for traffic users when choosing a particular means of transport. It is critical to the scale of traffic implementation, revenue, and overall business performance [4]. The total railway mileage in the world is about 1.5 million kilometers, and the European Union accounts for about 25% [5]. The rail is an important part of the railway. The defects on the surface of the rails have caused great damage to the wheelsets and bearings of the rail vehicles. When the

wheels are moving on the track with defective surfaces, periodic impacts will cause the coupled vibration of the entire vehicle and the track system. It will reduce the service life of the train components and a significant cause of vehicle derailment overturning and combustion axles. Therefore, defect detection of railway tracks is an essential means to ensure the safety of railway transportation. The annual railway inspection cost in the EU (European Union) alone is about 70 million euros [6]. Finding rolling contact fatigue (RCF) as early as possible cannot only avoid traffic accidents but also take timely measures to extend the service life of rails [7], both of which can reduce railway running costs [8]. The detection of track surface defects has long relied on manual inspections. This detection method needs experts to visually inspect components and use specific tools to identify any defects in the rail surface [9]. However, this method is cumbersome, hardworking, and prone to human error. In addition, the personal safety of the inspectors is also an issue, that needs to heed. With the increase in demand for high-speed railway transport and advanced technology, it is necessary to develop an automatic intelligent detection system to replace manual detection in detecting track surface defects.

Although the continual improvement of technology has reduced the probability of internal defects in the rail, the probability of fatigue cracks on the surface of the rail is still high [10]; harsh environments can also cause surface defects, which may irritate worsening the rail [11,12]. Surface defects of rail can be divided into the wave-shaped abrasion and discrete disease of the rail. Wave-shaped abrasion refers to the irregularity of the wavy shape of the periodic disease that appears on the surface of the rail in the longitudinal direction [13]. Discrete damage occurs randomly on the surface of the rail [14]. With developing technology, people have fully researched and applied the detection methods of rail surface defects by using the above technologies. Non-contact detection methods based on machine vision have gradually developed and been widely used in electrical, electronic, mechanical, automotive, and industrial inspections. Machine learning can even predict some regular damage.

This article reviewed the rail surface defect detection, recognition, classification, and evaluation methods proposed and improved in the past ten years. Technical analysis, the characteristics of technology, cost performance, accuracy, and the object to which the method is applicable. However, the results of each method and the matching limits are recorded. Through comparing and analysis methods that can evaluate the size or severity of rail surface defects or classify them to select the best rail surface damage detection method. The organization of this article is as follows: Chapter 2 expounds on the research results of detection and recognition, discusses and emphasizes the advantages and limits of each method in the paper. Chapter 3 introduces the research results of classification, evaluation, highlights the accuracy and background conditions of every method in the article. Chapter 4 discusses the results, analyzes the characteristics of the method, and

shows the overall progress in the field. Finally, Chapter 5 summarizes the purpose and results of this article, and prospects for detecting technologies.

2 Detection Methods

In the paper, the detection methods shown in 70 research papers regained by Scopus can be divided into six categories: geometry measuring, detecting wheel track motion (vibration or acceleration), using electric or magnetic field changes, using acoustic or light waves (thermal sensors), Image processing and machine learning. The research field is mainly concentrated in the emerging image processing and machine learning fields. Because other detection methods have been around for a long-time and have been thoroughly studied, the new research mainly explores improving detection technology and optimizes a particular step. In this section, a comprehensive review of these papers will be conducted. Analyze the performance, results, and limits of each technology.

2.1 Geometric Measurement

Although measuring geometric information can get the situation of the railway track through many indicators [15], good results have been achieved. A single geometric measurement method is used to obtain the geometric data of the track surface, mainly through a mechanical stylus or laser reflection. These methods can only detect a cross-section and cannot provide macroscopic inspection data. Later manual inspections are still required to confirm the location and size of surface defects, but most inspections in the railway industry do not use 3D reconstruction technology. To complete 3D technology combines cross-sectional data with a longitudinal plane positioning based on geometric detection, making 3D model reconstruction possible in defect detection on the rail surface. Ye et al. present a novel 3D perceptual system based on a low-cost 2D laser sensor [16]. This method uses the 2D laser sensor detection system and a drawing sensor to decide the longitudinal position movement. The data is formed into a three-dimensional point set. 3D modeling by Matlab. Use the 3D model to identify rail surface defects. Rikhotso et al. also applied this method to measure rail profile and detect defects on the track surface [17]. Casey Jessop and Naeimi each proposed a 3D modeling method combining the stylus Profile-metric and X-Ray scan data. The results showed a geometry similar to the squat network, also possible to infer the crack tip of the surface to a deeper depth that needs improvement. Still, the description of the mid-depth squat crack network is sufficiently accurate [18, 19].

The above methods can theoretically detect surface defects, but they also have obvious shortcomings. Radiography is mainly used to detect internal defects. Surface defects are just derived properties and cannot be quickly moved to detect.

The geometric detection of mechanical contacts also has this disadvantage. Laser sensors are sensitive to the environment, too strong light will affect the measurement results, and strenuous exercise will cause high deviations. Niu et al. proposed a method based on a binocular line scanning system, which can obtain contour information in the high-precision image while avoiding the decoding distortion of the structured light reconstruction method [20]. Sysyn et al. applied the modeling method to detect surface wear of turnouts, using the measurement data on the surface scanning device to establish the 3D model of the turnouts and analyze the change of the wheel/rail trajectory to detect the defect of turnouts [21]. This method has high 3D modeling accuracy while high detection speed, which is a research direction worth looking forward to.

2.2 Electromagnetic detection

Electromagnetic detection is a broad region of technologies used in railways. Due to surface inspection of blind subjects in conventional ultrasonic technology, an eddy inspection method based on electromagnetic principles has been proposed to detect the rail surface and near-surface defects [22]. Eddy testing uses alternating magnetic fields to create vortex-like induced alternating currents in the measured conductive Rail. The conductivity, magnetic permeability, defects, defect size, and shape of the measured part affect the distribution and size of the eddy. Through the coil-detection to measure the magnetic field change caused by the eddy. The distribution, size, and phase of the eddy in the test piece were measured without contact. It can perform high-speed inspections but has a skin effect and can only detect the surface and near-surface structure status of conductive materials [23]. The eddy testing technology has matured application examples in Eurailsout in Germany and Sperry in the United States [24]. However, lift-off has a more significant impact on the accuracy of rapid inspection. Huang and others, the Chinese Academy of Railway Sciences, and others have studied the card-type eddy sensor used to detect surface defects of curved turnout rails [25]. The research team of Nanjing University of Aeronautics and Astronautics has been continuously researching magnetic flux leakage detection technology in recent years. The team studied the development of array-type magnetic flux leakage inspection equipment and quantitative analysis of rail cracks to get defect location and distribution characteristics. Under the simulated conditions of the laboratory, the inspection speed of cracks with a width of 0.2mm can reach up to 200km per hour, which is in the leading position in the field [26]. This team added a ferrite in a sensor to reduce the reluctance to increase the magnetic intensity above the defects to increase the MFL signals [27]. It also gives an improved adaptive filtering method is proposed to solve the problem caused by filtering the MFL signal on the rail top surface [28].

The alternating magnetic field measurement method detects material defects by measuring the changes in the induced magnetic field on the surface of the Rail,

which can realize the accurate positioning and measurement of defects. The data Rows Handel collects from ACFM sensors are processed offline by combining threshold and feature matching methods rather than simple threshold methods. Even in the presence of peeling changes and noise, the automatic detection of surface damage defects has high reliability [29]. Chacón Muñoz et al. presents the B-Spline approach used for the accurate filtering of the noise of the raw ACFM signal gained during high-speed tests to improve the reliability of the measurements [30]. Papaeias et al. studied the applicability of ACFM technology in detecting and assessing the severity of surface cracked RCF defects [31]. ACFM technology has an extensive development prospect in detecting and quantifying RCF cracks. However, it is necessary to overcome the influence of the probe on the detection sensitivity caused by being too far from the object's surface. It is needed to continue improving the sensitivity of corrugated and polished track detection.

2.3 Track-side and On-board Vibration and Acceleration Detection

The dynamic interaction between the wheels and the track produces vibrations and varying accelerations transferred through the track system, air, and rolling stock. This vibration is generally used to measure rail defects in squats. Axlebox acceleration (ABA) measurement is often used to identify railway and track irregularities. The squat is a kind of rolling contact fatigue defect, and early detection is conducive to the safe operation of railways [32]. Mykola Sysyn et al. deal with measurement interpretation problems by analyzing vibration to estimate the health of the turnout [21]. Some scholars try to use this technology to detect spalling defects on the rail surface. Andrew Keong Ng aims to model and simulate three common defects with three degrees of damage, process and analyze the simulated RSD-driven ABA signal, and create explicit dynamic finite element models of wheel-rail interaction for tracks with and without RSDs [33]. Sysyn et al. introduced a method to detect the defect of the turnout by using the ESAH-F system to perform the machine learning on the inertial measurement data of the axle box on the running train [34]. The research team then discussed the Hilbert-Huang transform method used to overcome the relationship between the measured acceleration component and impact lateral distribution and the life cycle of ordinary turnout contact surface [35]. However, this detection method is challenging to use to detect cracks and small peeling. Besides, it is not practical outside the laboratory, because the vertical acceleration of the train in operation is affected by too many reasons.

2.4 Sound and Light Wave Detection

Acoustic wave detection uses the characteristics of sound wave reflection, diffraction, and transmission to determine whether there are defects inside the measured rail by watching the waveform, echo, sound velocity, attenuation, and resonance of the ultrasonic wave in the measured rail. Conventional ultrasonic technology has been widely applied in the detection of internal defects in steel rails. Defects extending in the horizontal direction and longitudinally close to the gauge angle will reflect the ultrasonic wave, and obstruct the incidence of the sound beam so that the dangerous cracks buried under it cannot be detected. There is a prominent detection blind zone, defects with a depth of less than 4mm from the surface of the tested part. There will be missed inspections. Therefore, ultrasound is generally not used for surface defect detection. However, Yi Jiang et al. and Hui Zhang et al. still tried to detect near-surface damage [36, 37]. The outstanding research is that Yuehong Zhang et al. studied the technology of rapid laser ultrasonic detection of rail surface defects and designed an interlaced laser ultrasonic defect detection imaging method: laser ultrasonic signals are excited on both sides of the rail to detect, and the images are fused and registered by algorithms. Filtering and image registration, obtaining a complete rail surface inspection image, displaying defect characteristics, and solving laser ultrasonic insensitive to defects [38]. Also, Bilawal Ramzan et al. proposed a research method to use Active Thermography to detect railroads surface crack [39]. The reflection of microwaves can be used to measure distance. Andrey Zhuravlev et al. proposed using the microwave or short waves to detect the rail surface, but it has become a method [40].

2.5 Image Processing Detection

Accurate judgment and cognition through computer vision research have been applied in many fields with the development of science and technology. The basic principle of rail computer visual damage detection is to use an image acquisition device to obtain information on the surface of the rail and convert it into an electronic image signal. By filtering the image, the contrast and equal processing are enhanced. According to the data characteristics of the pixel, the interference will interfere with various code operations. The background information is eliminated, and the characteristics of the rail surface damage, such as size, length, number, etc., are extracted. It even uses deep learning to mine the potential features of the data to classify and judge damage. The basic computer vision inspection system, the important part of the composition, includes the image acquisition module, the image-the preprocessing module, and the result judgment module. The research in computer vision also focuses on the optimization and exploration of these three modules. Usually, an inspection system is constructed by combining the improved methods of all stages. Liu and Wei presented a

detection system based on image processing and edge detection to find the defect on the rail surface [41–44].

About improving the image acquisition module, it is mainly to adopt better equipment and optimize the method of acquiring images. The more creative research is that Francisco Javier de la Calle Herrero etc. proposed a system that uses visual algorithm processing to find changes in pixel values between images [45]. Besides, Jia Ge et al. present an improved traditional system by combining a speed adaptive (SAA) system to adjust the appropriate exposure frequency and uniform image quality at any time according to the speed of the vehicle [46]. Guangyu Dai et al. studied an image processing system that is useful for online real-time detect the defects of the railway track surfaces. When the images are obtained by linear CMOS camera, the train detection speed can be 50 km/h while the image is a planar array CMOS camera; the train speed can be 100 km/h [47].

More researches focus on the image-processing module and the defect recognition module. The irregularity of rail surface defects makes automatic visual inspection very difficult. Because irregular defects appear randomly on the surface of the rail, the defects can only be located according to the image pixels. Moreover, in the natural environment, the uneven illumination and different reflectivity received by the curved surface of the rail will greatly impact the grayscale distribution of the image. The electronic interference in the image acquisition process will inevitably add some noise to the image [48]. At the same time, effective image enhancement and automatic threshold segmentation of defective images can improve detection efficiency. The image processing process mainly goes through the following steps. First: Track positioning, using the principle that the track surface and the background are quite different, such as edge detection, gray value positioning [49], etc. Second: Image noise reduction, the commonly used noise reduction methods are: mean filtering, median filtering, non-local means, Gaussian filtering, etc. Third: Image enhancement, traditional methods are global histogram equalization, adaptive histogram equalization, contrast-limited adaptive histogram equalization [50], local contrast enhancement [51], low-rank matrix decomposition, etc. At Last: Threshold segmentation, commonly used methods are: Ostu, Maximum between-class variance method, maximum entropy method, Iterative threshold method, etc.

The research on image processing has mainly improved and innovated on the original methods. Li et al. propose the Michelson-like contrast (MLC) measure image enhancement method with a new threshold algorithm, named proportion emphasized maximum entropy (PEME) [46]. Wu and Li optimized the background difference method by reducing the template preprocessing to reduce the influence of shadows and a loop threshold algorithm using histogram judgment [52]. Jinrui Gan et al. proposed a background-oriented defect detector (BODI), which uses modeling to determine specific image features of the track to distinguish background and defects to improve detection efficiency. The perfect detection rate of 100% for large defects, but only 41.78% for relatively small

defects [53]. The defect-recognition rate reached 92.2%. Yu et al. proposed a coarse-to-fine model (CTFM) to identify defects of different scales. Using different image processing methods to identify various defects has achieved better results than the previous method. The accuracy rate reached 100% in the actual evaluation [54]. Hu et al. proposed an optical rail surface spalling detection algorithm based on visual saliency. Use a two-dimensional differential Gaussian (2D DoG) filter to reduce noise [55]. Wu Yunpeng et al. proposed the LWLC-GSME model in a drone-based visual inspection system, using a new image enhancement algorithm based on local Weber-like contrast (LWLC) to enhance railway images and gray-scale stretched maximum entropy (GSME) segmentation images [56].

The image processing method of visual inspection shows better performance than other detection methods in detecting the rail surface peeling damage. However, in practical applications, it may be affected by more factors to reduce the accuracy. Therefore, some new image processing technologies have also been used. For example, Ashwani Kumar Dubey proposed using the maximally stable extremal region marking on the original system [57]. In the turnout surface wear detection field, Sysyn et al. introduced the application of computer vision in the diagnosis of common cross frogs [58]. However, technology has insufficient detection accuracy in detecting the rail surface cracks or more minor defects. With the continuous research of computer machine learning, the efficiency and accuracy of machine learning methods in image classification have surpassed the traditional classification methods. Since 2010, many scientific research institutions have conducted a lot of research on the categorization of rail surface defects in this field and make specific predictions about the development of cracks or defects. Machine learning methods are necessarily accompanied by defect assessment and prediction, so they are introduced in the next section.

3 Classification Evaluation and Prediction

Advances in technology have made it possible to automatically classify or evaluate the damage to the track surface, whether it is based on ultrasonic inspections or, of course, more visual images. Now the final evaluation and classification step almost have to rely on machine learning. Current methods for predicting features of track defects and even more minor cracks must also use machine learning. This section mainly introduces some research results in this field in the past ten years. Machine learning is divided into deep learning and shallow learning methods. The shallow machine learning calculation logic is relatively simple, and the classification analysis of available features is more accurate. Deep machine learning is more complex and has advantages in the classification and analysis of uncertain features

3.1 Shallow Machine Learning

The traditional data classification method is a shallow machine-learning model. The basic process of using image information classification is as follows: First, image features are extracted. Commonly used image features include HOG (Histogram of Oriented Gradient) features [59], LBP (Local Binary Pattern) features [60], HAAR features, and SIFT (Scale Invariant Feature Transform) features [61]. After extracting the feature words, use the word bag model or clustering method (Marker controlled watershed segmentation (MCWS), K-means (KM) clustering, Expectation-Maximization (EM), and canny edge detection (CED), etc.) to reshape extracted features. Then send the reshaped features to the classifier to get the classification result. Commonly used classifiers include support vector machines (SVM), decision trees, random forests, and Bayesian classification. Mercy et al. introduced three machine-learning methods for the prediction of track surface defects. Decision trees have the highest accuracy in predicting distortions and inhomogeneity. The random forest has the highest accuracy in predicting specific defects [62]. Regardless of accuracy, the recognition rate and complexity of the detection task. Machine learning has reached or even surpassed traditional methods.

Table 1 summarizes some research on the detection and judgment of track surface defects using image processing methods and the recently studied shallow machine learning methods. Shallow machine learning can already perform evaluation tasks other than the detection of rail surface defects, such as classification. Nearly 90% of the classification tasks of multi-class classification have been well applied in practice. With the research and development of deep learning, the effect of deep learning in target detection tasks surpasses all the above methods. And people gradually turn to the study of deep learning rail surface defect detection.

3.2 Deep machine learning

The deep learning model can learn deep abstract features layer by layer from the data set through supervised and unsupervised modes to achieve an abstract description of learning goals. The concept of deep learning has been produced since 1986. Deep learning models can learn deep abstract features layer by layer from the data set through supervised or unsupervised learning methods to achieve abstract descriptions of learning goals. In 2016, Hinton et al. elaborated on the deep learning system and proposed related technologies such as deep neural networks. In recent years, the wave of deep learning research has come and has produced many significant results.

Table 1

Image Processing and machine learning methods for rail defect detection

Method	Features	Dataset	Results	Ref.
Decision Tree	Rail surface defect	Data from East Coast Railway division	Precision= 93.02%	[62]
Random Forest			Precision= 95.23%	
Region growing	The area of defect	Rail Images Acquisition	Sensitivity=100%	[63]
MCWS			Sensitivity=90.9%	
K-means			Sensitivity=72.7%	
Canny edge			Sensitivity=81.8%	
SVM	Crack	17000 Rail images from CRH and CM	Accuracy=99.87%	[64]
Random Forest			Accuracy=100%	
logistic regression			Accuracy=99.74%	
boosted tree			Accuracy=99.92%	
AdaBoost multiclassifier +CART decision tree	Rail surface defect classifier recognition	1200 rail images	Recognition rate(%): Scale peeling crack=81.45; Stripping block =79.64;Tread cracks=82.27	[65]
Deep Forest	Peeling and Crack classification	Video from X5 PTZ camera	Classification accuracy =100%	[66]
LWLC+GSME	$25 < T-I \text{ Defect} < 255 \text{ mm}^2$; $T-II > 255 \text{ mm}^2$	HD video from DJI Matrice 600	T-I Precision=88.63.22%; T-II Precision=90.32%	[56]
GMM+MRF	Rail surface defect	Image detection system	Precision =88.8%, recall =92.0%	[67]
Bayesian classification + EM	Onboard detection RUL prediction	Data from 3D acceleration sensors	RUL predicted accuracy=75%	[68]
MODWPT+ Lasso regression	Trackside detection RUL prediction	Data from 3D acceleration sensors	RUL predicted accuracy=50%	[69]

The deep learning models currently used in the field of image and visual recognition mainly include Stacked auto-encoders, SAE, Deep belief network, DBN, and Convolutional Neural Networks, CNN), among which CNN has achieved satisfactory research and application results. A multi-layer convolutional

neural network (convolutional neural network, CNN) can adaptively input data for feature learning and classify or recognize the learned features. CNN-based target detection is mainly divided into three categories: regression-based network models, such as YOLO, network models generated based on candidate regions, such as R-CNN, Fast R-CNN, Faster R-CNN; search-based network models, such as AlexNet; and VGGNet. Since deep learning simulates the human visual perception system, avoids the weaknesses of manual design features, and has the advantages of non-linearity and high parallelism, it has a wide range of applications.

There have also been a lot of researches in the detection of rail surface defects. The surrounding set is the RSDD data released by Beijing Jiaotong University. By combining Wavelet Scattering and Neural Networks, Yang Jin improved classification accuracy up to 97.20% and 94.74% for the two datasets [70]. Combining the advantages of the bilateral full convolutional network and CRF proposed by Zhang Ziwen and others will also significantly improve detection accuracy [71]. This article introduces the use of deep learning, mainly neural convolution, to detect rail surface defects in the past ten years. Part of the research on classification and evaluation is shown in table 2. Various methods can be intuitively compared.

3.3 Prediction

The losses caused by the catastrophic railway failures caused by RCF are difficult to estimate. Although the rails are very expensive, the defects are found in time, and the prediction and evaluation are carried out. The forecast reduces the number of inspections and avoids disasters, which is an economical and safe method. In the field of state prediction, many methods of finite element analysis are used. For example, H.M. El-Sayed establishes a wheel-rail stress model, simulates the rail head's damage state through finite element analysis, and predicts the service life of the rail through long-term data [72]. The ability of machine learning in the field of prediction has also been proven to have more potential. In recent years, there have been more studies for the prediction of rail damage. Ahmed Lasisi et al. proposed an integrated learning framework. It takes advantage of the advantages of a single machine learning tools and overcomes assuming basic distribution (such as Weibull) to predict the deviation of the defect, and also consider the railway characteristics except for the traffic volume (Mt) to achieve the purpose of optimizing the prediction results [73]. Sysyn's research team conducted two studies on the remaining useful life (RUL) prognosis of common crossings as shown in Table 2 on the inspection data obtained by the on-side and the on-board intrinsic measurement system of the turnout.

The two machine learning methods proposed in the research systematically carry out the processes of feature extraction, selection, fusion, and degradation modeling and are then used to deal with the problem. It corresponds to about

50% and 75% of the condition indicator reached. Therefore, the available period would be sufficient for maintenance planning, thus avoiding operational hindrance costs [66].

Table 2
Deep learning detection methods

Method	Features	Dataset	Results	Ref.
DCNN	Classification: Weld, large, middle and small Squat; Joint	22408 images; size 100 × 50	Accuracy=92%	[74]
CNN	Defect on Surface	25.000 profiles per second	Accuracy=98%	[75]
CNN	Defect on Surface	7897 images size 4096x3000	Precision=61.14%; Recall=75.52%	[76]
Cropped i-CNN	Rail Surface location	5793 images; size 960 × 1280	Recall=92.54%; Precision=92.8%	[77]
MOLO	Classification: corrugation, fatigue block, stripping off block	96944 images; size 224×224×3	Corrugation AP=95.28%; Fatigue block AP=84.60%; Stripping off block AP=82.33%	[78]
SegNet	Rail surface defects	120 rail training images; size 1250 × 55	Detection Rate=100%	[79]
YOLOv3	Rail surface defect	184 images; size 416 × 416	Recognition rate more than 97%	[80]
MRF-GMM and CNN	Rail surface defects	6 categories, 2700 samples; size 250 × 160	Precision=96.74%, Recall =94.13% Overlap =95.18%	[81]
DCNN	Detection and classification of abrasion scar crack corrugation	38000 training images; size 512×512	The accuracy of defect classification achieves 96.55%	[82]
Faster R-CNN	Rail surface defect	1000 images in environments	Average Precision =97.8%	[83]
OC-IAN & OC-TD	Rail surface defect	RSDDs	T-I: pre.=84.21%; T-II: pre.=91.76%	[84]
RBGNet & LWLC-ME	Rail surface defect	video images resized to 1280 × 720	Precision over 90%	[85]
Mcnet	Rail surface defect	3936 NRSD images,; size 400 × 400	Manmade Pre.=85.28% Natural Pre.=72.74%;	[86]

4 Results and Discussion

In this article, various methods for detecting railway surface defects are discussed. The detection of defects on the rail surface is challenging because the cracks have an irregular form and have no specific shape or size. Each detection method may have some advantages and some disadvantages. However, visual inspection and electromagnetic technologies such as ACFM and MFL have significant benefits in comprehensively comparing inspection efficiency and accuracy. In terms of detecting speed, both methods can be used to obtain data on a running train. However, the sensitivity of electromagnetic technology at high speeds is not high. ACFM is generally less sensitive to short or shallower discontinuities than traditional eddy currents. MFL cannot detect relatively small defects. From the distribution of the number of papers, it can also be shown that more scholars are engaged in the research of visual inspection, especially the visual inspection direction in machine learning, on rail surface defects.

The visual inspection method of image processing has been well certified in the laboratory, but in the actual environment, there is a lot of external interference, different texture characteristics, changing lighting conditions, and stains on the rails, etc., will cause the image processing process significant interference reduces the accuracy of detection. The shallow machine learning methods shown in Table 1 have achieved 90% or more accuracy in defect detection. Even for some major defect categories, the accuracy can reach 80%. The deep machine learning shown in Table 2 further strengthens this effect. The detection accuracy is further improved by 5-7%. Many neural convolution processes are combined with other image processing or SVM, random forest, and other machine learning methods to achieve better detection results. Many methods have proved the feasibility and relative accuracy in real track surface damage detection. Enlarging the data set can avoid overfitting of the model and enhance the accuracy of detection. But larger data sets require more data collection time and investment, and deep machine learning requires a lot of computing time in working hours and also has high requirements for computing equipment. The method of deep machine learning in the classification of rail surface damage has shown considerable prospects. There are still very few studies used to predict the surface defect of railroad tracks, and the prediction results are also relatively unstable. The primary research method does not use deep machine learning because shallow machine learning methods are easier to control the number and focus of features.

Conclusions

This article focuses on reviewing the most advanced rail surface damage detection methods in the past decade. These results have been published in top journals and conferences. We reviewed the criteria of the 70 research articles screened after the application and checked their content in detail. These articles are evaluated based on the detection methods they use, performance results, and limitations. Through

analysis, we can infer that machine learning visual inspection methods can be widely used to detect railway surface defects. Combining multiple methods with sub-gradient detection of different types of defects has a better detection effect. More research needs to focus on the detection of rail surface cracks. At present, satisfactory results have been achieved for spalling and squats, while relatively small surface crack research has hardly made significant progress. For the reasonably complicated in 3 classifications task, orbital surface defect classification accuracy can reach 75% or even 85%. After more data sets and more research results to overcome false defects or even minor defects are proposed in the future, the accuracy of classification will be further improved. In the future, research on crack damage detection on the surface of the steel rail will mainly focus on the optimization and improvement of deep machine learning, especially in the field of CNN. The research on detection can be extended in the direction of evaluating the defects and then predicting the service life of the rail. More image processing methods suitable for real environments are also necessary.

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