International Journal of Internet, Broadcasting and Communication Vol.14 No.3 149-154 (2022)
http://dx.doi.org/10.7236/IJIBC.2022.14.3.149

IJIBC 22-3-18

Current Trend and Direction of Deep Learning Method to Railroad Defect Detection and Inspection

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Abstract

In recent years, the application of deep learning method to computer vision has shown to achieve great performances. Thus, many research projects have also applied deep learning technology to railroad defect detection. In this paper, we have reviewed the researches that applied computer vision based deep learning method to railroad defect detection and inspection, and have discussed the current trend and the direction of those researches. Many research projects were targeted to operate automatically without visual inspection of human and to work in real-time. Therefore, methods to speed up the computation were also investigated. The reduction of the number of learning parameters was considered important to improve computation efficiency. In addition to computation speed issue, the problem of annotation was also discussed in some research projects. To alleviate the problem of time consuming annotation, some kinds of automatic segmentation of the railroad defect or self-supervised methods have been suggested.

Keywords: Deep Learning, Railroad Defect, Defect Detection, Annotation.

1. INTRODUCTION

Train is one of the most popular forms of public transportation. Therefore, unexpected accidents and delays are considered serious for railways, which make maintenance process essential. Previous researches report that rail fractures are often caused by defects in rail surface or rail fastener. Defects are caused by various reasons, for example, friction or the collision of parts in railroad tracks, which naturally increase over time [1, 2]. This growing defect can cause risk factors such as broken rails. Therefore, it is very important to guarantee that the risk of the rail and its fasteners are minimized so that the safety and stability of train operation can be maintained. As a way to ensure the safety and stability of train, railroad inspection and maintenance should be operated regularly and accurately [3]. Currently, the inspection of the rail and the fasteners on the railway track is mainly operated by railway staff. Although this process is simple and does not cost much, we also have to consider its low efficiency in detection and relatively high missing rate, especially when the railway staffs feel fatigue. In recent years, automatic defect detection based on computer vision has been proposed and widely tried in industry [4–7]. Computer vision based methods are now being employed to detect the defects of rails

Manuscript Received: June. 19, 2022 / Revised: June. 22, 2022 / Accepted: June. 24, 2022
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and inspect the railroad condition, so that the high cost of the inspection by railroad investigation staff and low efficiency could be alleviated. Automated defect detection and segmentation can help investigators find rail defects. As the need to automate the railroad inspection process has increased, the related researches have been undergoing to accelerate the automation of the railroad surfaces analysis using computer vision. Concerning automatic railroad defect detection, lots of researches that applied computer vision method have been done [8-10]. For example, He et al. introduced the Perona–Malik diffusion model for a rail surface defect detection system [11]. And Gan et al. proposed a hierarchical inspection framework including coarse extractors and fine extractors to handle different railway elements [12]. In recent years, the application of deep learning technology in image processing has achieved great success. Thus, many research projects have also applied deep learning technology to railroad defect detection. In this paper, the researches that applied computer vision based deep learning method to railroad defect detection and inspection have been reviewed, and the current trend and the direction of those researches were discussed.

2. RAILROAD DEFECT DETECTION AND ANNOTATION

2.1 Railroad defect detection

The image based deep learning method is extensively researched nowadays, and it is also applied to railroad defect detection. Railroad defect detection is basically performed by image inspection. Railroad images are feed to deep neural network and the neural network detects or classifies the defect on the railroad surface. In many cases, the defect of fasteners is also inspected as well. To operate in real time, the speed of the calculation is considered important. For example, YOLOv5 was used to localize the fasteners and the rail [13]. The authors modified YOLOv5 to operate even in low-performance devices, suggesting Ghost bottleneck module [14]. Then, rail images were fed into Mask R-CNN to detect and segment the defect [15]. The fasteners were fed into ResNet to classify whether the fasteners are normal, loose or broken. They reported that their method achieved 99.68% mean average precision(mAP) at 97.9 frame per sec(FPS). In other case, three different size deep convolution neural networks were applied that were designed by themselves to classify normal, weld, squats, and joint, and it was concluded that the good performance can be at the cost of computation time [16]. Their network showed about 92% detection accuracy. In other research, MobileNet was modified to suggest MobileNetV2 and MobileNetV3 for fast computation [17]. In the modified model, they used bottleneck block with a depth-wise separable convolution layer. This block first increases the number of channels, and then reduces the number of channels to decouple the spatial information from the channel information. By doing this, they reduced the computation time at the cost of just slight decrease of accuracy. Their modified MobileNetV2 and MobileNetV3 detected corrugation, fatigue block detection, stripping off block and showed good performance with fast computation time. It produced about 83% mAP at 55-110 FPS. Likewise, modified YOLOv4 network was applied, of which MobileNetV3 was used as the backbone network [18]. By using MobileNetV3, they could increase the performance at the cost of negligible increase in calculation. However, the application of MobileNetV3 led the optimization of the number of parameters, and the overall detection speed was improved. The proposed method was tested on the database created by the authors, and showed that the proposed method could effectively detect rail surface defects, mAP 88% at about 42-43 FPS [18]. In other research, they transformed the input images to handcrafted pyramid features of multiscale to reduce the dimension of the input data [19]. This input data were fed into light-weight CNN to classify the railroad defect. Because the dimension of the input data was reduced, classification network did not require many parameters, and the number of training data could be also decreased. They reported that their suggested method showed F-measure about 85%. In other research, the authors applied GraphCut theory to segment the railroad defect, and used YOLOv2 to localize the railroad defect precisely [20]. They reported that the proposed method resulted in average accuracy of 97.11%. Giben et al. proposed a deep convolution neural network for material classification and segmentation of rails [21]. And FaghihRoohi et al. proposed a deep convolutional neural network (DCNN) for classification [22]. UAV was used to acquire the images of railway, and FCN-8 based segmentation was used to detect split defect on the rail head, combined with heuristics [23, 24]. It showed detection rate of about 80%. Similarly, rail surface segmentation and surface defect detection method were suggested for UAV [25]. They modified ResNet for low quality images, and suggested hybrid loss consisting of binary cross entropy(BCE), structural similarity index measure (SSIM) and intersection of union(IoU). Their method resulted in F-measure of 0.967. As a summary, Figure. 1 shows the general processing of the researches mentioned above. The input image is fed to object detection module with preprocessing such as intensity normalization. In object detection module, the background in the input image is removed and the target objects are enhanced. The results of the object detection module are fed to segmentation or classification module. The defect of railroad is segmented in segmentation module to draw the boundary of the defect. In classification module, the type of rail defect is classified or the state of the fastener is determined.

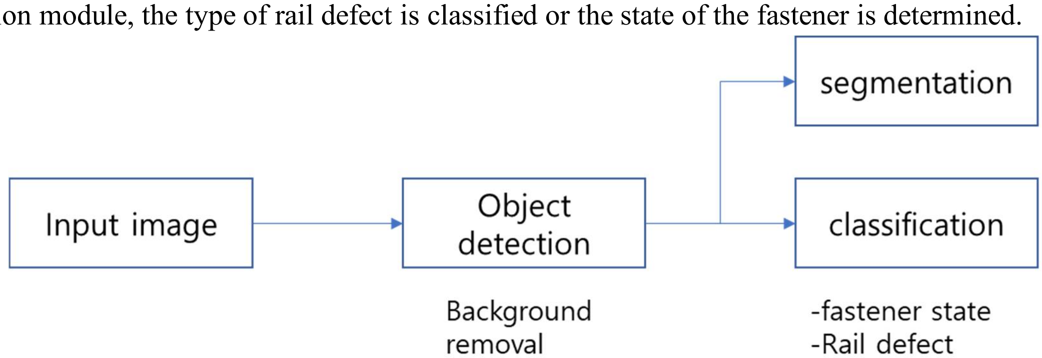

Figure 1. Railroad defect detection overview

2.2 Annotation for Railroad defect detection

The image based deep learning method generally requires extensive amount of annotated images, which is labeled images which would train the deep learning network how to differentiate the target and the rest. To acquire the annotated images, it costs time consuming labor and inspection. Especially, the railroad images are very homogeneous, and the ratio of defect or broken part of the railroad is very small. Thus, the annotation process for railroad defect can be very tedious and time-consuming work with low efficiency. Therefore, researches to reduce or alleviate the cost of annotation have been proposed. For this purpose, fastener template for fastener detection was applied [26]. If the distance between the input region of the image and the template is close enough, then the region was considered as true fastener and added to the training data. In this way, they constructed near-automatic annotation for the fastener in the rail. This method can be very efficient because the railroad images are relatively homogeneous without much variation. In other research, they used a modified autoencoder to reconstruct the input railroad images, and the residual between the reconstructed images and the original images was considered as the defect [27]. To enhance the learning process of the defect, the authors added artificial defect on the original input images. By this method, they alleviated the cost of annotation, resulting in self-supervised railway surface defect detection. Likewise, handcrafted features were used that discriminate the defect from the background [19]. They compared the average intensity of a column in the railroad data image with the pixel intensity, assuming that the intensity values of defect are lower than the average intensity. By this assumption, they thresholded the defect region, alleviating the annotation problem. Similarly, GraphCut was applied to segment the railroad defect automatically, and the segmented results could be considered as annotated data [20].

3. CONCLUSION

Reviewing the previous researches, it could be noticed that the image based railroad defect detection methods are developing rapidly. We have reviewed the researches that applied computer vision based deep learning method to railroad defect detection and inspection, and have discussed the current trend and the direction of those researches. They are largely targeted to operate automatically without visual inspection of human. The railroad images could be acquired by UAV or trail attached to trains. The acquired images were preprocessed to eliminate the background and enhance the rail image. In some cases, handcrafted features were extracted from the rail image to localize the target image, and in other cases, deep learning based object detection methods were used to localize the target image. The localized images were fed into another deep learning based classifier or object detector. The reported accuracy values were over 80%, which seems to be able to reduce the necessity of human visual inspection on the railroad images. The proposed methods were targeted to operate in real time. Therefore, methods to speed up the computation were also investigated. In most researches, the method to reduce the number of parameters in CNN was suggested. To operate deep learning based method, large amount of labeled images is required. The annotation process, which is labeling, requires time-consuming and tedious work of human inspector. To alleviate this problem, some kinds of automatic segmentation of the railroad defect or self-supervised methods have been suggested. This kind of methods may reduce the time cost used in annotation, and increase the possibility to operate in real situation.

ACKNOWLEDGEMENT

This research was supported by a National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIT) (NRF-2021R1F1A1049467) and by Korea National University of Transportation in 2022.

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