NaSTech

JOURNAL OF NATURAL SCIENCES AND TECHNOLOGIES
2022, 1(1), pp. xx-xx, DOI: xx.xxxx/xxxxx.xxxxxxxx

Deep Learning Advancements in Railway Track Segmentation: Previous Studies and Improvements

Turan TEYMURBAYLI[1], Utku KAYA[2,*]

[1] Railway Systems Engineering Department, Eskişehir Technical University Eskişehir, Turkey

[2,*] Vocational School of Transportation, Eskişehir Technical University Eskişehir, Turkey

ABSTRACT

This article focuses on investigating the utilization of deep convolutional neural networks for segmenting railway tracks. Deep learning, which aims to simplify data processing by emulating human intelligence on computers, plays a significant role in this regard. Railway tracks are widely recognized for their importance in railway transportation. Consequently, ensuring track integrity requires thorough surface scanning. However, considering the extensive expanse of railway tracks, manual scanning proves to be a challenging and time-consuming task. Railway track segmentation serves as a fundamental step in identifying track defects, enabling easier detection by extracting tracks from surrounding images. This article discusses various studies conducted in this field and provides insights into the advantages offered by each approach.

Keywords: Deep learning, Railway track segmentation, Convolutional neural networks

1. INTRODUCTION

Defects in railway systems can arise from a single flaw or from compound flaws. Compound flaws are more complex and encompass multiple elements, making their detection and evaluation more challenging than that of a single flaw (Sresakoolchai, Kaewunruen, 2021) [1]. Currently, rail failures can generally be categorized into three broad groups:

1. Defects originating from manufacturing flaws in the rails - a classical example being the head-check defect, typically caused by hydrogen-induced cracking in the rail head.
2. Defects resulting from improper handling, installation, usage, or damage. An example of this is the wheel burn defect caused by skidding, which is one of the common rail failures.
3. Defects stemming from the fatigue degradation of rail steel over time, such as transverse cracks or buckling.

The most frequently encountered types of rail defects are as follows: internal nuclear defect in the rail head, central nuclear defect in the rail head, external nuclear defect in the rail head, crack in the bolt hole, crack beneath the bolt hole (Xu, Zhao, Yu, Wang, & Shen, 2020) [2].

Localized or extensive wearing of the rail surface poses a significant risk to train safety, potentially leading to derailment. Flaws occurring at the rail connection points, particularly in bolt holes, and longitudinal cracks in the rails are factors that affect the integrity of the rails and contribute to crack propagation. Large cracks, in particular, can cause rail fracture or excessive deformation. Isolated transverse fractures resulting from rail defects have a low likelihood of causing derailment. Even continuously welded rails subjected to thermally induced high forces can experience transverse fractures, typically not exceeding 30 mm in winter months and even less at other times. However, transverse fractures ultimately lead to loss of load-bearing capacity and induce a tendency for wheel climbing. This results in deformation of the rail movement, leading to misalignment of rail ends and an increased risk of derailment.

Traditionally, the detection of rail surface defects has relied on manual inspection. However, the manual inspection method requires significant resources and human power while exhibiting low detection effectiveness. Consequently, various defect detection methods have been developed. These include eddy current coil detection (Song, Yamada, Shitara, & Takemura, 2011) [30], detection using ultrasonic surface waves (Chen, Wang, He, Yu, Zhang, & Wang, 2022) [3], MEMS gyroscope sensors (Boronakhin, Podgornaya, Bokhman, Filipenya, Filatov, Shalymov, & Larionov, 2011) [4], magnetic induction (Antipov, Markov, 2019) [5], and image processing (Liang, Zhang, Liu, He, & Zheng, 2018) [6]. Machine learning, which has been widely utilized recently, is also a non-destructive inspection method (Sresakoolchai, Kaewunruen, 2021) [1]. However, despite the improvement in detection accuracy achieved by these methods, non-destructive detection may not always yield precise results and does not guarantee 100% accuracy. Therefore, non-destructive detection results should be verified with alternative methods or confirmatory tests.

2. RELATED WORKS

One of the crucial issues in ensuring passenger safety is the periodic inspection and monitoring of railway tracks (Gibert, 2016) [7]. The inspection of the railway line based on computer vision techniques and the automatic detection of errors on the railway line using image recognition have increased passenger safety by reducing human errors and allowing more frequent inspections (James, 2018) [8]. Regulations in the United States require frequent inspections of railway tracks, typically once or twice a week (Gibert, 2016) [7]. Traditional railway inspection is carried out by railway personnel walking along the tracks or using a low-speed rail inspection vehicle (Gibert, 2016; James, 2018) [7-8].

However, research on the automated inspection of tracks has been conducted for approximately 20 years (Zahran and Al-Nuaimy, 2004; Chan and Burrow, 2009; Guler, 2014; Giben, Patel, and Chellappa, 2015; Zhao, Mittal, and Rao, 2017; James, 2018; Guo, Qian, Wu, Leng, and Yu, 2021; Meng, Kuang, Ma, and Wu, 2022) [9-13, 8, 14-15]. The first successful application of Fully Convolutional Networks (FCNs) was performed by LeCun et al., and a architecture called LeNet5 was developed (Lateef and Ruichek, 2019) [16]. Subsequently, Alex Krizhevsky developed a deep convolutional neural network called AlexNet. AlexNet is a deepened and extended version of the LeNet neural network (Lateef and Ruichek, 2019) [16]. After adjusting the structure of AlexNet, ZFNet was introduced (Zeiler, Fergus, 2014) [17].

Before the era of deep learning, many methods similar to partial differential equation-based methods were used. For example, the Fully Convolutional Network (FCN) proposed by Long, Shelhamer, and Darrell (2015) [18] achieved an improvement of 20% relative to the average IU of 62.2% for PASCAL VOC, NYUDv2, and SIFT Flow segmentation while taking less than 1/5 of a second for inference on an image.

Giben (2015) proposed deep convolutional neural networks (DCNNs) for visual inspection on grayscale images. This neural network, designed using semantic segmentation and material classification, was tested to be more accurate and resilient to noise compared to manually designed learning machines. The network was run in a feed-forward manner and outperformed other networks. Additionally, the proposed network achieved 93.35% material accuracy using 10 material classes [12].

Segmentation involves assigning a label to each pixel to divide the image into different regions (Qi, 2016; Zhang, Song, Xu, He, Niu, and Yan, 2020) [19]. Fully convolutional neural networks have been further developed for segmentation, utilizing various methods for better extraction of contextual information and optimization of obtained information (Zhang, Song, Xu, He, Niu, and Yan, 2020) [20]. Existing networks such as AlexNet, GoogLeNet, VGG, and ResNet have been adapted and enhanced for segmentation, with improvements made (Long, Shelhamer, Darrell, 2015; Garcia-Garcia, Orts-Escolano, Oprea, Villena-Martinez, and Garcia-Rodriguez, 2017) [18], [21].

Most fundamental segmentation networks use an encoder-decoder structure that combines feature extraction and task layers to perform segmentation (Li, Zhu, Yu, Guo, and Wan, 2020) [22].

Various methods are used in many studies in the literature. Some of these deep convolutional neural networks include MobileNet and YOLOv3 (Yuan, Chen, Liu, Lin, and Luo, 2019) [23], YOLOv3 (Yanan, Hui, Li, and Hang, 2018) [25], VGG19 (Kim, Lee, and Han, 2020) [26], and SegNet based on the backbone network (Liang, Zhang, Liu, He, and Zheng, 2018) [6].

These neural networks also employ different prediction techniques. The YOLOv3 algorithm uses dimensional clustering to accurately and quickly detect targets (Yanan, Hui, Li, and Hang, 2018) [25], while the MOLO model can predict rail surface defects using a single-stage regression network with reduced computation and a multi-scale structure (Yuan, Chen, Liu, Lin, and Luo, 2019) [23].

Defects on the rail surface are a significant factor affecting operational safety. Unfortunately, the accuracy of rail surface defect detection systems is limited, and image processing methods have not been fully tailored for railway lines. The lack of existing neural networks poses challenges in detecting blurry rail edges. The RGBNet rail boundary guidance network proposed by Wu, Qin, Qian, Guo, Wang, and Jia (2022) aims to overcome these issues. This architecture, which effectively utilizes the complementarity between the rail surface and rail boundary, adds high-level rail surface object information through progressive fusion. The system combines precise edge features at different layers with rail surface features to predict the rail surface. Additionally, this architecture was developed without loading models from pre-trained data [24].

In the study conducted by Li, Zhu, Yu, Guo, and Wan (2020), a deep multi-task learning-based algorithm was used for rail segmentation. This network can automatically identify alarm zones on the rails. The escape point segmentation and SEB modulation module were used to train this network. For training, 5,400 images were collected from three different sources, and 1,000 images were used for testing [22].

NaSTech
JOURNAL OF NATURAL SCIENCES AND TECHNOLOGIES
2022, 1(1), pp. xx-xx, DOI: xx.xxxx/xxxxx.xxxxxxxx

Date	Author	Subject	Algorithm	Accuracy
2018	Yanan, Song, et al. [25]	Rail Surface Defect Detection	YOLOv3	99%
2019	Yuan, Hao, et al. [23]	Rail Surface Defect Detection	Molo	95.28%
2019	Wang, Yang, et al. [27]	Determination of rail boundary	Simplified CNN	99.25%
2020	Kim, Hyeonho, Suchul Lee, and Seokmin Han [26]	Railway surface defect segmentation	Downgrade of an FCN based on VGG19	90%
2020	Zhang, Defu, et al. [20]	Surface defect segmentation of out-of-service rail	MCnet	71.07%
2021	Bojarczak, Piotr, and Waldemar Nowakowski [28]	Segmentation of railway track surface	FCN-8	89.8%
2022	Yang, Han, et al. [29]	Railway segmentation	RT-GAN	81.34%
2022	Wu, Yunpeng, et al. [24]	Rail surface segmentation and surface fault detection	RBGNet	94.7%

Table 1. Studies in the literature

There are very few articles specifically examining rail surface segmentation in the literature. Some of the conducted studies are shown in Table 1. Therefore, it is believed that the study conducted within the specified scope will contribute to the literature.

3. CONCLUSION

This article presents significant advancements in the segmentation of railway tracks using deep learning. The conducted studies focused on the segmentation of rails and connection elements using deep learning techniques with data collected from various sources. Many of these studies primarily addressed rail defects. However, our study aims to train deep neural networks using data gathered from the internet. The importance of our research lies in its direct applicability to railway tracks.

The capabilities of deep neural networks in deep learning enable improvements in rail segmentation. With these advancements, we anticipate an increase in the success rate of rail segmentation. We believe that significant progress can be achieved in the segmentation of railway tracks by employing deep neural networks, leading to enhanced efficiency.

In conclusion, railway track segmentation is a crucial method for railway management, safety, and efficiency. This approach enables railway operators to engage in better planning, utilize resources more effectively, and enhance the performance of railway tracks.

REFERENCES

[1] Sresakoolchai, J., & Kaewunruen, S. (2021). Detection and severity evaluation of combined rail defects using deep learning. Vibration, 4(2), 341-356.
[2] Xu, Q., Zhao, Q., Yu, G., Wang, L., & Shen, T. (2020, July). Rail defect detection method based on recurrent neural network. In 2020 39th Chinese Control Conference (CCC) (pp. 6486-6490). IEEE.
[3] Chen, Z., Wang, Q., He, Q., Yu, T., Zhang, M., & Wang, P. (2022). CUFuse: Camera and ultrasound data fusion for rail defect detection. IEEE Transactions on Intelligent Transportation Systems, 23(11), 21971-21983.
[4] Boronakhin, A. M., Podgornaya, L. N., Bokhman, E. D., Filipenya, N. S., Filatov, Y. V., Shalymov, R. B., & Larionov, D. Y. (2011). MEMS-based inertial system for railway track diagnostics. Gyroscopy and navigation, 2, 261-268.
[5] Antipov, A. G., & Markov, A. A. (2019). Detectability of rail defects by magnetic flux leakage method. Russian journal of nondestructive testing, 55, 277-285.

[6] Liang, Z., Zhang, H., Liu, L., He, Z., & Zheng, K. (2018, July). Defect detection of rail surface with deep convolutional neural networks. In 2018 13th World Congress on Intelligent Control and Automation (WCICA) (pp. 1317-1322). IEEE.
[7] Gibert, X., Patel, V. M., & Chellappa, R. (2016). Deep multitask learning for railway track inspection. IEEE transactions on intelligent transportation systems, 18(1), 153-164.
[8] James, A., Jie, W., Xulei, Y., Chenghao, Y., Ngan, N. B., Yuxin, L., ... & Zeng, Z. (2018, December). Tracknet-a deep learning based fault detection for railway track inspection. In 2018 International Conference on Intelligent Rail Transportation (ICIRT) (pp. 1-5). IEEE.
[9] Zahran, O., & Al-Nuaimy, W. (2004). Automatic segmentation of time-of-flight diffraction images using time-frequency techniques application to rail-track defect detection. Insight-Non-Destructive Testing and Condition Monitoring, 46(6), 338-343.
[10] Zhao, J., Chan, A. H. C., & Burrow, M. P. N. (2009). A genetic-algorithm-based approach for scheduling the renewal of railway track components. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 223(6), 533-541.
[11] Guler, H. (2014). Prediction of railway track geometry deterioration using artificial neural networks: a case study for Turkish state railways. Structure and Infrastructure Engineering, 10(5), 614-626.
[12] Giben, X., Patel, V. M., & Chellappa, R. (2015, September). Material classification and semantic segmentation of railway track images with deep convolutional neural networks. In 2015 IEEE International Conference on Image Processing (ICIP) (pp. 621-625). IEEE.
[13] Mittal, S., & Rao, D. (2017). Vision based railway track monitoring using deep learning. arXiv preprint arXiv:1711.06423.
[14] Guo, F., Qian, Y., Wu, Y., Leng, Z., & Yu, H. (2021). Automatic railroad track components inspection using real-time instance segmentation. Computer-Aided Civil and Infrastructure Engineering, 36(3), 362-377.
[15] Meng, S., Kuang, S., Ma, Z., & Wu, Y. (2022). MtlrNet: An effective deep multitask learning architecture for rail crack detection. IEEE Transactions on Instrumentation and Measurement, 71, 1-10.
[16] Lateef, F., & Ruichek, Y. (2019). Survey on semantic segmentation using deep learning techniques. Neurocomputing, 338, 321-348.
[17] Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part I 13 (pp. 818-833). Springer International Publishing.
[18] Long, J., Shelhamer, E., & Darrell, T. (2015). Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 3431-3440).
[19] Qi, G. J. (2016). Hierarchically gated deep networks for semantic segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 2267-2275).
[20] Zhang, D., Song, K., Xu, J., He, Y., Niu, M., & Yan, Y. (2020). MCnet: Multiple context information segmentation network of no-service rail surface defects. IEEE Transactions on Instrumentation and Measurement, 70, 1-9.
[21] Garcia-Garcia, A., Orts-Escolano, S., Oprea, S., Villena-Martinez, V., & Garcia-Rodriguez, J. (2017). A review on deep learning techniques applied to semantic segmentation. arXiv preprint arXiv:1704.06857.
[22] Li, X., Zhu, L., Yu, Z., Guo, B., & Wan, Y. (2020). Vanishing point detection and rail segmentation based on deep multi-task learning. IEEE Access, 8, 163015-163025.
[23] Yuan, H., Chen, H., Liu, S., Lin, J., & Luo, X. (2019, October). A deep convolutional neural network for detection of rail surface defect. In 2019 IEEE vehicle power and propulsion conference (VPPC) (pp. 1-4). IEEE.
[24] Wu, Y., Qin, Y., Qian, Y., Guo, F., Wang, Z., & Jia, L. (2022). Hybrid deep learning architecture for rail surface segmentation and surface defect detection. Computer-Aided Civil and Infrastructure Engineering, 37(2), 227-244.
[25] Yanan, S., Hui, Z., Li, L., & Hang, Z. (2018, November). Rail surface defect detection method based on YOLOv3 deep learning networks. In 2018 chinese automation congress (CAC) (pp. 1563-1568). IEEE.
[26] Kim, H., Lee, S., & Han, S. (2020). Railroad Surface Defect Segmentation Using a Modified Fully Convolutional Network. KSII Transactions on Internet & Information Systems, 14(12).
[27] Wang, Y., Zhu, L., Yu, Z., & Guo, B. (2019). An adaptive track segmentation algorithm for a railway intrusion detection system. Sensors, 19(11), 2594.
[28] Bojarczak, P., & Nowakowski, W. (2021). Application of Deep Learning Networks to Segmentation of Surface of Railway Tracks. Sensors, 21(12), 4065.
[29] Yang, H., Li, X., Guo, Y., & Jia, L. (2022). RT-GAN: GAN Based Architecture for Precise Segmentation of Railway Tracks. Applied Sciences, 12(23), 12044.
[30] Song, Z., Yamada, T., Shitara, H., & Takemura, Y. (2011). Detection of damage and crack in railhead by using eddy current testing. Journal of Electromagnetic Analysis and Applications, 2011.