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EFFICIENT PAVEMENT DISTRESS DETECTION AND VISUAL MANAGEMENT IN LEAN CONSTRUCTION BASED ON BIM AND DEEP LEARNING

Ting Deng[1] and Yi Tan[2]

ABSTRACT

With a wide range of road construction worldwide, the focus of road engineering has shifted to road maintenance and management. This paper presents a research aimed at developing a lean management framework that integrates BIM and deep learning technology to guide lean production applications in road maintenance management. Firstly, the pavement distress dataset is established based on the obtained road point cloud data. Secondly, a deep learning-based 3D object detection network is applied for automatically detect the pavement distress and improve the accuracy and reliability of the detection. After obtaining the detection information of the distress, Dynamo is utilized to realize the efficient visualization management of pavement distresses. Finally, an untrained road section is applied for the experiment. The predicted information of distress is integrated and visualized in BIM model can provide a better maintenance guidance and well promote the transformation of pavement intelligent maintenance management.

KEYWORDS

Lean construction, template, formatting, instructions, references.

INTRODUCTION

Infrastructure maintenance is crucial for ensuring the safe and efficient functioning of roads, bridges, and other structures. For example, as large-scale roads are built and operated over time, there will be exhibited a range of distresses, including cracks, potholes, and so on. These distresses may directly reduce the driving comfort and safety (Zhong et al, 2022), affect the performance and normal service life of the road, and even lead to serious traffic accidents. Therefore, it is significant to detect the pavement distress efficiently and accurately for the pavement maintenance.

Traditional pavement distress detection methods include manual inspections, visual assessments. However, these methods are often time-consuming, labor-intensive, and may be not able to provide the detailed information for making accurate evaluation. To improve the efficiency and reliability of pavement distress detection, the concept of lean construction is introduced. Lean construction is an approach that focuses on reducing waste, streamlining processes, and improving efficiency. This concept is particularly important in the pavement distress detection and management process for more efficient analysis of road pavement

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conditions. In fact, with the development of computer vision technology, there has been a significant amount of research on image-based pavement distress detection over the past few decades. This automated pavement distress detection technology can greatly improve the efficiency and accuracy of distress detection. However, image-based road data lacks depth information and cannot clearly express the spatial relationship of pavement distress.

With the cost reduction of 3D data acquisition devices, 3D laser scanning technology has gradually become an important ways of road data acquisition. The 3D point cloud data collected by this technology can obtain the depth information of pavement, and is not easily affected by the environment, making it an effective data source for improving the accuracy and reliability of pavement distress detection. Although some 3D data-based pavement distress detection algorithms (Guan et al, 2021; Huang et al, 2014; Jiang & Tsai, 2016; Li et al, 2017; Ouyang & Xu, 2013; Zhang, Wang, et al, 2017a, 2017b) have achieved certain success in recent years, most of these methods convert point cloud data into other forms and do not fully leverage the advantages of point cloud data. On the other hand, point cloud-based object detection algorithms have been widely used in fields such as autonomous driving and have achieved good results. However, at present, point cloud-based object detection is mainly tested on some public large-scale datasets [30], and has not yet been implemented in pavement distress detection task. In addition, there is limited research on effectively managing distress information by further connecting detected road distresses to the real world.

Therefore, in order to directly apply 3D point cloud data to automate pavement distress detection and improve the lean effectiveness in road maintenance, this paper proposes a framework that integrates lean management into pavement distress detection and visualization management based on 3D laser point cloud data, deep learning methods, and BIM. The proposed method aims to automatically detect pavement distress through deep learning methods to improve accuracy and reliability, and then visualize the detected results in BIM environment to improve management efficiency.

This paper is organized as follows. Section 2 reviews the literature of lean concepts, pavement distress detection, and BIM-based pavement maintenance management. Section 3 introduces the detailed information of the proposed method. Section 4 used an experiment to demonstrate the applicability of the proposed method, and finally, Section 5 has the conclusions and future work.

RELATED WORKS

LEAN CONCEPT IN THE CONSTRUCTION INDUSTRY

The principles of lean thinking are based on the lean production philosophy originated by the manufacturer Toyota and developed under the guidance of engineer Taichi Ohno(Howell, 1999). The underlying philosophy of lean production theory is to minimize costs, materials and time(Anandh et al, 2021), and evaluate working practice to eliminate unnecessary activities while preserving or increasing value(Chen et al, 2012). The idea of Lean concepts originated in the manufacturing industry, but have since spread to the construction industry. At first, the goal of lean construction was to apply manufacturing principles by standardizing processes. However, practitioners and researchers soon discovered the dynamic nature of construction project management and adapted their approach to fit the unique requirements of each stage of the project(Hamdar et al, 2015). Shou et al (2021) develop a lean management framework for guiding lean production applications in the oil and gas industry. Forbes et al. explored the management of roadway safety from a Lean perspective and put forward methods to prevent accidents and eliminate related wastes(Forbes & Ahmed, 2010).

The purpose of Lean Construction (LC) is to eliminate non-value adding activities, also known as waste, in construction projects and increase the value for relevant parties. The implementation of LC principles can result in substantial improvements in road maintenance projects where the impact of delays can be severe and affect all parties involved. Despite this, traditional approaches in infrastructure asset management have yet to fully embrace lean thinking in their planning for road maintenance (Mohammadi et al, 2022). Therefore, this paper combined lean principle to improve the pavement maintenance in distress detection and visualization management.

PAVEMENT DISTRESS DETECTION USING INNOVATION TECHNOLOGY

Traditional method of manually detecting pavement distress is time-consuming, inefficiency, and low accuracy. With the amount of pavement maintenance continues to increase, there is a significant need for automatic distress detection technologies which can improve the detection efficiency and accuracy. (Zhong et al, 2022). Over the past decades, there have been various researches focused on image-based pavement distress detection. Traditional approaches for pavement distress detection using image algorithms include edge detection-based methods (Zou et al, 2012), threshold-based segmentation methods (Wang & Tang, 2011),et al. However, these methods are Those methods are greatly impacted by the presence of shadows and varying lighting conditions in images, leading to negative detection results.

In the past few years, deep learning-based methods have been extensively researched in pavement distress detection, particularly the deep convolutional neural networks (CNNs) (Zhang, Wang, Li, et al, 2017). These methods have proven that the CNNs to be more efficient and stable than other traditional machine learning detection methods. For instance, Li et al (2020) used a CNN-based method on 3D pavement images to detect pavement distress and demonstrated the suitability of CNNs in classifying defects on pavement images. However, the focus of these methods aimed at classifying of the pavement distress without location information. Therefore, object detection methods have been introduced to enable the precise estimation of distress features. Du et al (2021) used the YOLO network to predict both pavement distress category and location using the information from road images in complex environment. Ibragimov et al (2022) proposed a pavement distress detection method based on Faster R-CNN and applied it to a full-size pavement image framework which allows to reduce the sliding window size and enable to detect cracks in larger images. Despite the high accuracy achieved by existing image-based pavement distress detection methods, there are still some limitations. The detection effect is inevitably limited under complex road conditions such as varying light and shadows. Furthermore, pavement images lack depth information and unable to express the spatial relationship of distress clearly.

With the development of 3D laser scanning technology, it is easier to obtain road point cloud data. This kind of data is not affected by shadow and light, and also contains the depth information and can express the spatial positions and geometric dimensions (Medina et al, 2014). Several researches have explored the application of point cloud data for pavement distress detection. Zhang, Wang, et al (2017a) proposed a 3D shadow modelling method to transform the original point cloud data into binary images which combined with noise suppressing algorithms to attain the target descended patterns. Tan and Li (2019) have utilized road images from UAV oblique photogrammetry to reconstruct road 3D point cloud models. However, there methods either manually extract features or process 3D pavement data from a 2D perspective before applying 2D-based deep learning methods for distress detection. Therefore, this research attempts to directly utilize the 3D point cloud data for automatic pavement distress detection by using the deep learning method which can improve the detection accuracy and generalization capability.

BIM-BASED PAVEMENT MAINTENANCE MANAGEMENT

In recent years, the advancement of pavement inspection techniques has brought attention to the optimal solutions for data management. The traditional approaches of Pavement

Management Systems are inadequate to exploit the potential of this information, particularly for visualization and infrastructure modelling (Bosurgi et al, 2021), which can be addressed by using BIM. In practice, BIM is widely used in the processes and activities of construction projects to improve the outcome of lean production, but its application during the operation and maintenance stages remains limited. D'Amico et al (2022) demonstrated the possibility of creating a digital twin model by combining geometric and design information with monitoring results obtained from road infrastructure. Bosurgi et al (2020) attempted to apply BIM in road maintenance management by incorporating survey data related to road conditions into the I-BIM model, resulting in a more efficient and simpler management system. However, it was a preliminary experimental approach, and the detected distresses were not visually presented to provide maintenance guidance. Therefore, this paper aims to enhance the efficiency of pavement maintenance management by visualizing pavement distress using BIM.

METHODOLOGY

The proposed framework integrates the concept of Lean to increase the efficiency and accuracy of pavement distress detection and management. The process consists of three parts and the framework is shown in Figure 1. The first step involves collecting point cloud data and preprocessing it to create a labeled dataset for network training. Second, a 3D object detection method-PointPillar(Lang et al, 2019) is applied to detect pavement distress. Finally, the results are integrated into a pavement BIM model by using Dynamo to establish families of pavement distresses and visually manage the detected distresses. By continuously improving the accuracy of distress detection and efficient visualization management, this method will drive the transformation towards a more intelligent and effective pavement maintenance system.

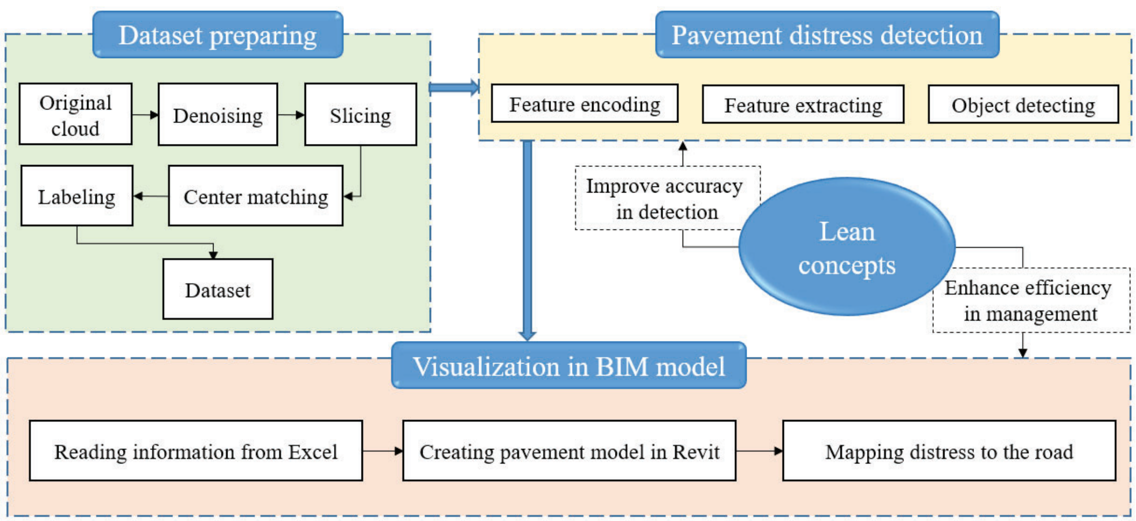

Figure 1: Workflow of pavement distress detection and visualization

ESTABLISHMENT OF PAVEMENT DISTRESS DATASET

This paper applies the vehicle-mounted LiDAR system to acquire pavement point cloud data and the types of pavement distress include transverse crack, longitudinal crack, alligator crack and pothole. Before sending point cloud data into neural network for training, the data needs to be preprocessed and annotated to create the dataset. The process of point cloud data processing is shown in Figure 2.

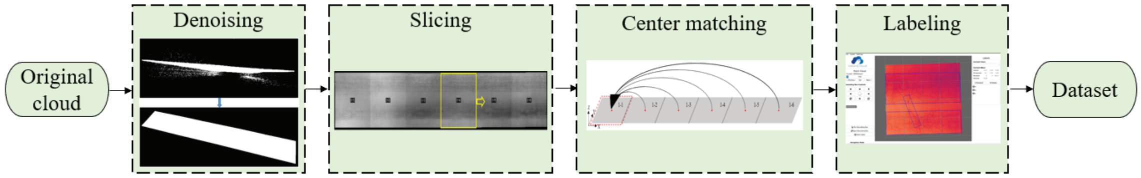

Figure 2: Data processing flow

The original point cloud data contains a large amount of noise and other less useful points, which can negatively affect the accuracy of detection results. To address this problem, this study combined two different methods to filter out the noise. The first method used is passthrough filtering, which is applied to eliminate the noise present in a wide range above the road surface. This method works by removing points that have values outside the given range in the specified dimension. After rough denoising, the statistical outlier removal (SOR) filter is used to remove noise more finely. The SOR filter calculates the average distance of each point to its K nearest neighbors. Assuming that the distance of all points in the point cloud data conforms to a Gaussian distribution, with its shape determined by the mean μ and standard deviation σ, the distance d from the nth point P_n (X_n, Y_n, Z_n) to any other point P_m (X_m, Y_m, Z_m) is calculated as follows:

$$d = \sqrt{(X_n - X_m)^2 + (Y_n - Y_m)^2 + (Z_n - Z_m)^2} \quad (1)$$

$$\mu = \frac{1}{n}\sum_{i=1}^{n} Si \quad (2)$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Si - \mu)^2} \quad (3)$$

After denoising, the collected pavement point cloud data need to be divided into smaller one to adapt the training requirement of network model due to the limited computing resources. In this paper, in order to reduce the computational cost during model training, the full-scale point cloud is divided into many smaller size blocks by using a sliding window with size of 4×4 m^2. These smaller blocks are indexed to represent different sections of the road, and rough registration is necessary to ensure that the coordinate values of the point cloud blocks fall within the same range, which can provide more standardized data for neural network model training. Finally, the point cloud labelling tool is used to label the category and position of distresses with 3D bounding boxes and created the pavement distress dataset.

Deep Learning-based Pavement Distress Detection

The aim of pavement distress detection is to classify and localize pavement distress automatically based on collected point cloud data, and provide specific information for pavement maintenance and management. The network architecture used in this study is called PointPillar(Lang et al, 2019) which offers a balance between speed and accuracy in 3D object detection algorithms. The implementation of PointPillar involves three main steps and the framework is shown in Figure 3.

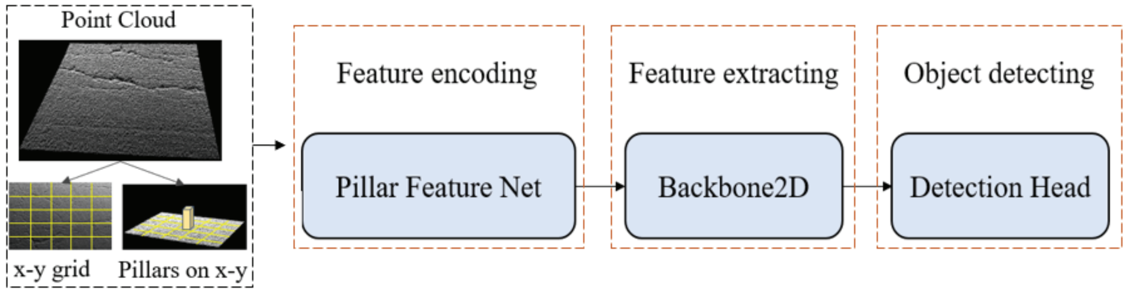

Figure 3: The detection framework of PointPillar

The first step is feature encoding. The point cloud is divided into a grid in the x-y plane and pillars are created with unlimited z extent. The points in each pillar are then represented as a 9D tensor. The input data is then sent through a linear convolution, transforming the 9D feature to 64D. Max-pooling is performed to create an output tensor of size (C, P). Finally, the encoded features are transformed into a pseudo-image by scattering them back to the original locations.

The second step is feature extracting. The backbone of PointPillar has two subnetworks: one is a top-down network that produced features with sufficiently small spatial resolution and this process can be represented by a series of blocks with Conv2D (C_{in}, C_{out}, k, s, p), where C_{in} and C_{out} are represented the input and output channels, k, s , and p are represented the kernel size ($k \times k$), stride size, and padding size respectively. The other one is a upsampled network with $Deconv2D$ (C_{in}, C_{out}, k, s, p), and each 2D convolutional layer followed by BatchNorm and ReLU sequentially. Finally, the upsampled features are concatenated to constitute high resolution feature map.

The third step is object detecting. After the feature map is extracted by the backbone network, the detection head is used to predict 3D bounding boxes of distress. The approach involves setting default boxes for each category, and each default box with two rotations and one scale which can roughly represent the dimension characteristics of different distresses. The default boxes are then matched with ground truth using 2D IoU and the shape offsets and confidence for all object categories are predicted. The height of the bounding box is not used for matching, but rather as an additional regression target.

BIM-based Pavement Distress Visualization and Management

After the distresses are detected by PointPillar, Dynamo is utilized to visualize the pavement and distress in BIM environment. This process simplifies the representation of the pavement in the realistic 3D environment, and specific routines have been coded for distress mapping to the pavement model, which can provide more intuitive information for road maintenance. To visually manage the detected distress in BIM environment, the pavement BIM model is created according to the collected point cloud data in this study. Then, the projected images of various distresses from point cloud are converted into maps by the method of generating ground, and their morphology and related parameter information can be shown in BIM environment. The procedure is shown as Figure 4.

This section mainly includes creating a node program by using Dynamo which is capable of reading data from Excel spreadsheet that contains the detected pavement distress information. Then according to the geometry and coordinate information of different distresses, the distribution scope of length and width on the pavement is calculated, and a number of points with corresponding X and Y coordinates can be generated based on the scope matrix. Finally, the pavement distresses were created in the BIM model for visual management.

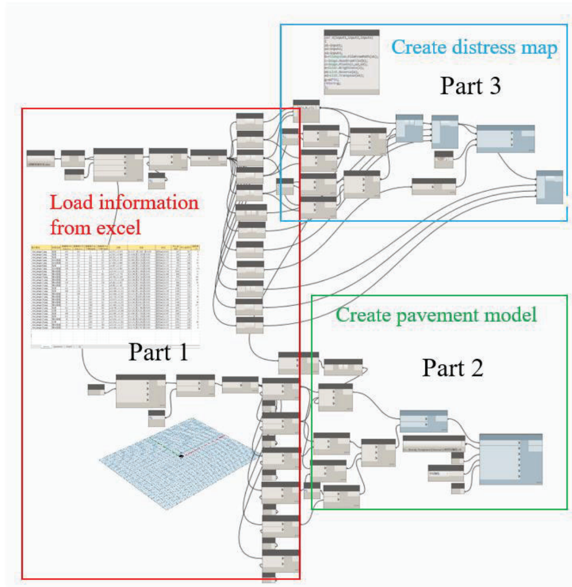

Figure 4: Visual programming to generate model in Dynamo

The Application of the Lean Concept

The implementation of lean principles in the proposed method is based on the idea of continuous improvement. The solution uses a combination of advanced technologies, including deep learning and BIM, to streamline the pavement distress detection and visualization management process. By using the 3D object detection network PointPillar to automatically detect pavement distress, the solution reduces the time and effort required for manual inspections. Additionally, the use of BIM for visualization of the pavement and distress allows for a more efficient and effective management of the pavement, as the information is presented in a clear and intuitive manner.

The method also incorporates a proactive approach to maintenance, which is an important aspect of lean principles. By detecting pavement distress early and visualizing it in BIM, maintenance can be planned and executed more efficiently, reducing downtime and the potential for safety hazards. In addition, this study provides specific information about the pavement distress such as dimension and location, which can be used to inform maintenance and management decisions and continuously improve the process.

EXPERIMENTS AND RESULTS

To demonstrate the practicality of the proposed method, the prepared dataset is used for the model training, and then the trained model is used to detect the distress on a new complete road section. After obtaining the detected information of the distress, Dynamo is successfully applied to map the distress to the road model in BIM. And the detailed information of the distress can be viewed in the attribute column, which provide efficient and effective guidance for pavement maintenance.

The Experiment Setting

To carry out the experiment, high performance workstations are utilized with the following specifications: 4 NVIDIA GeForce RTX 3090 GPUs, 1 Intel Xeon Sliver 4210R CPU, and a Linux system to set up the training environment. The detected network PointPillar is initially designed mainly for use in the field of autonomous driving, and all experiments are based on the KITTI object detection benchmark dataset (Geiger et al, 2012) which consists of both lidar point clouds and images. Therefore, before model training, some details need to be adjusted to adapt the detection task of pavement distress. Firstly, the custom $Dataset$ need to be developed, and the most important step is to load prepared training data, then the annotated point cloud coordinate system must be adjusted to the Lidar coordinate system through a simple transformation, with X, Y, and Z being the inputs for the network and x, y, and z being the label coordinates and d being the height of the Lidar sensor.

THE RESULT OF PAVEMENT DISTRESS DETECTION

The trained model is utilized to detect the pavement distress and predict 3D bounding boxes for each object with a confidence score. Figure 5 shows the detection results and different colored 3D bounding boxes represent different distresses. Compared with the ground truth, the predicted result of the trained model has a good performance.

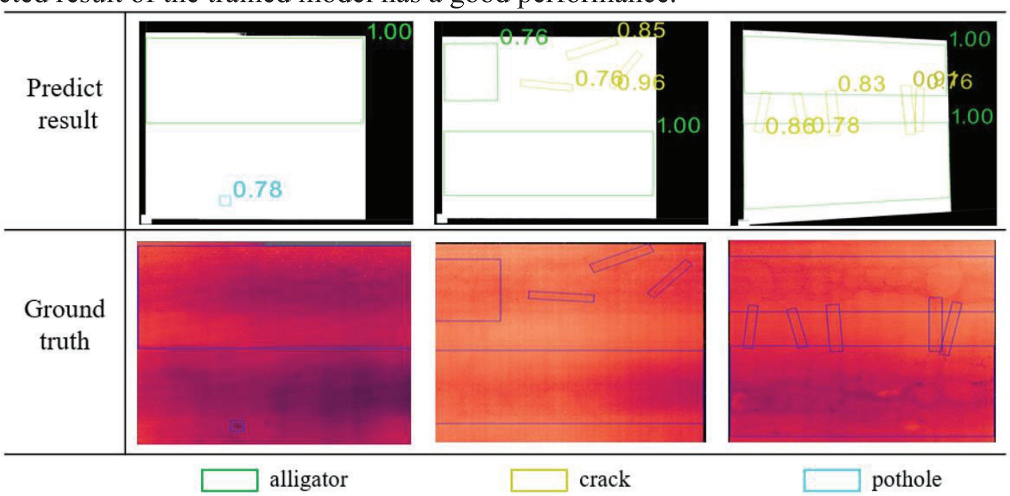

Figure 5: The comparison between predict result and ground truth

Then, the features of the distress including dimension and location information of the predicted 3D bounding boxes are extracted and stored in the spreadsheet. A portion of the collected information is shown in the following Table 1. The experimental results demonstrate that the 3D object detection algorithm based on point cloud data applied in the field of autonomous driving, as presented in this paper, has been successfully applied to automatic pavement distress detection, exhibiting both logical and functional correctness, and possessing certain practical value.

Table 1: Pavement Distress Information

Point cloud index	Class	Center coordinate X(mm)	Center coordinate Y(mm)	Rotation （rad)	…
1	Alligator crack	207	307	3.1408	…
2	Alligator crack	204	89	3.1323	…
.	.	.	.	.	
.	.	.	.	.	…
.	.	.	.	.	
26	Pothole	2191	139	4.1863	…
27	Transverse crack	2324	226	3.1565	…
28	Transverse crack	2449	204	3.1356	…

The Result of Pavement Distress Visualization

After preparing the information of pavement distress, Dynamo is used to read and import those data into Revit for modelling. As described in Section 3.3.3, the pavement model is established first and the detail information of the pavement is shown in the Table 2.

Table 2: Pavement parameters

Length(mm)	Width(mm)	Material	Original point
2480	392	asphalt	(0,0)

Finally, based on the coordinate and dimension information, all the distresses are created and mapped on the pavement with different colours representing different types. The parameters of each distress will be displayed in the attribute column and the visualization results are shown in Figure 6. After the successful modelling of pavement distresses, road managers can use the information query function of Revit to view the coordinates and dimensions quickly and analyze the distribution of the defects efficiently, and provide intuitive and reliable information for road maintenance.

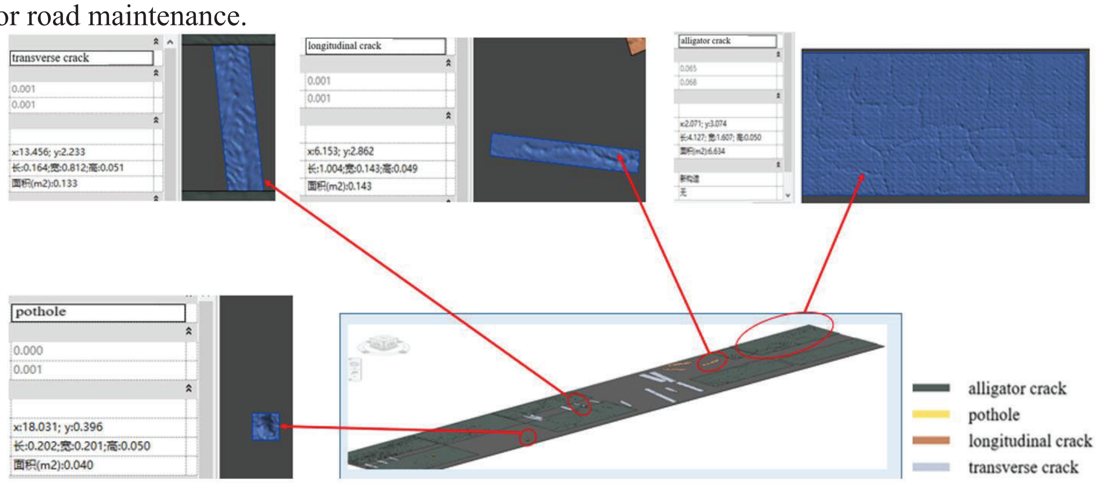

Figure 6: The visualization result of pavement distress

CONCLUSIONS AND FUTURE WORK

With the increasing total mileage of road maintenance management worldwide, traditional manual methods and two-dimensional inspection processes are no longer able to meet practical needs, and more efficient and reliable new technologies must be introduced. The advantage of 3D point cloud data makes it a potential method to improve the accuracy and reliability of road maintenance for detecting and quantifying the pavement distress. Therefore, a framework for automatic pavement distress detection and visualization management by using point cloud data, a deep learning-based 3D object detection algorithm, and BIM technology is proposed to improve the efficiency and effectiveness of pavement distress detection and visualization management.

Firstly, the collected point cloud data are pre-processed and a dataset of pavement distress is established. Then, the deep learning-based 3D object detection model PointPillar is applied to detect the distress automatically. After obtaining the detection information of the distress, Dynamo is utilized to realize the visualization of pavement distresses. In conclusion, the method utilizes advanced technologies to automate and streamline the process, while also incorporating a proactive approach to maintenance and a focus on continuous improvement.

However, in this study, the point cloud labelling process is manual and time-consuming which lead to a heavy workload. Therefore, a semi-automatic point cloud annotation method will be explored to reduce the burden of labelling. In addition, while the current 3D object detection method can achieve distress classification and localization, the extracted geometric features for severity assessment are region-level. To improve accuracy, point-level segmentation will be considered for more accurate distress quantification in the future.

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