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Innovative method for recognizing subgrade defects based on a convolutional neural network

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HIGHLIGHTS

- Accuracies of cascade and multi-stage CNNs classified subgrade defects according to training and validation results satisfy the requirements for subgrade assessment.
- Strategy using classifier 2 in cascade CNN improved robustness of object recognition in images obtained at different transmitting frequencies.
- CNN-based method using cascade CNN exhibited highly robust subgrade defect detection performance under various conditions compared with Sobel edge detection and K-value clustering analysis.

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ABSTRACT

Subgrade defects originate below the base of an asphalt pavement and they contribute significantly to pavement damage. The detection of subgrade defects is considered challenging because the recognition of defects is difficult. Therefore, the utilization of ground penetrating radar (GPR) to detect subgrade defects has attracted significant interest in recent years. However, the use of manually processed GPR images for classifying defects is inefficient and inaccurate. Thus, in this study, we applied convolutional neural networks (CNNs) to GPR images for automatically classifying subgrade defects (e.g., uneven settlement, sinkholes, and subgrade cracks). Two CNNs called multi-stage CNN and cascade CNN with different structures were established to accomplish the tasks automatically. The main difference between the two CNNs is that the cascade CNN is a classifier 2, which is for recognition and trained only using hard samples. Each CNN was developed in training, validation, and testing processes. Based on the training and testing results, sensitivity analysis was performed to verify the stability of the CNNs. We compared state-of-the-art methods for defect detection and the CNN-based method in order to verify the superior performance of the CNNs. Finally, we tested an application of the CNN-based method to show that it is transferrable to other asphalt pavements. The training results indicated that the cascade CNN classified subgrade defects with 97.35% accuracy during training and 96.80% in validation, while the multi-stage CNN classified subgrade defects with 91.35% accuracy during training and 90.45% in validation. The sensitivity analysis results showed that the cascade CNN exhibited the expected stability in terms of the transmitting frequency, i.e., the frequency of a high-frequency electromagnet wave from the transmitting antenna of the GPR, and different highway structures, whereas the multi-stage CNN did not. In addition, compared with Sobel edge detection and K-value clustering analysis, the CNN-based method obtained more robust performance at subgrade defect detection under various conditions using raw images. These results indicate that the CNN-based method performs well and it can classify subgrade defects in realistic situations.

1. Introduction

The subgrade of an asphalt highway is an important component and the main part responsible for bearing loads on the pavement, including the pavement's weight and the vehicle load [1]. Due to the stress state of the subgrade, some defects are inevitable such

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as uneven settlement, sinkholes, and subgrade cracks [2]. Subgrade cracks always occur in the subgrade before propagating to the surface but these subgrade defects cannot be observed directly. However, these defects always lead to pavement stresses and they affect the performance of highways. If effective measures are taken early to detect these defects in the subgrade, then the formation of pavement distress may be prevented. However, the detection of these defects is very challenging, mostly because they are located below the pavement.

In recent years, several innovative technologies have been used to detect subgrade defects, such as ground penetrating radar (GPR) technology [3–5], X-rays [6], and ultrasonic flaw detection [7]. GPR technology has some advantages such as its high efficiency, safe operation, nondestructive operation, and high anti-interference level. Therefore, GPR has been used widely to detect and evaluate highway structures. Significant progress has been made in the utilization of GPRs for detecting defects in subgrade structures, but this technology has several obvious disadvantages, i.e., its dependency on other auxiliary instruments for damage recognition, complicated data preprocessing requirements, and the difficulty of automatic defect recognition [8]. For example, Dong et al. [9] used a novel vehicle-mounted GPR to estimate the thicknesses of highway structure layers and to detect defects. The estimated results showed that the system and methods obtained satisfactory accuracy. This method must be assisted by a global positioning system and filtering algorithms. Khamzin et al. [10] used an air-launched GPR system comprising two truck-mounted GSSI antennae driven at near-highway speeds to assess highway structures and defects, but defects must be classified manually based on GPR data in this process. Szymczyk et al. [11] utilized an innovative S-transformation and successfully re-constructed GPR signals into three-dimensional models by using a complex conversion process. Yuri et al. [12] used the common offset and common midpoint method based on GPR data to analyze the composition of soil. Tosti and Benedetto [13] predicted pavement pumping using GPR, although this method can only recognize pavement pumping. In general, highway detection, especially subgrade defect detection, demands the development of an automatic defect recognition system that can use GPR data or images directly.

The methods described above partially address the aim of using GPR data or images but the following problems remain: (1) complex foreground, background, and feature information related to subgrade defects in GPR data cannot be handled easily; (2) the robustness of the algorithms can be affected by variable real-world situations (e.g., transmitting frequency of the GPR and the highway structure); and (3) human assistance is required to recognize the defects in images or data. Therefore, it is important to develop an automatic subgrade defect recognition system with sufficiently robust performance in variable real-world situations and under the influence of GPR noise.

Developments in machine learning have led to deep learning, especially convolutional neural networks (CNNs), which obtain good performance in the field of object recognition [14,15]. Lecun et al. [16,17] proposed the CNN as a type of artificial neural network with a structure where shared weights reduce the complexity of the network model. The structure is similar to that of biological neural networks [18–20]. Detailed information about CNNs can be found in previous studies [21–27]. In general, robustness is an attractive property of CNNs in civil engineering, where this robustness is evident in terms of their high stability at recognizing different objects such as humans and animals in different conditions. This property is important for defect recognition in GPR images where it is necessary to handle complex foreground, background, and defect features. Therefore, CNN can be utilized to classify different subgrade defects. In the last two years, CNNs have been used to detect highway defects, where Tong et al. [28] and Cha et al. [29] employed CNNs to detect pavement cracks, while Cha et al. [30] used a fast CNN to detect multiple visual damage types in structures. The results of these three studies demonstrate that CNNs exhibit good stability in this field compared with conventional detection algorithms. Tong et al. [8] also used CNNs for the recognition, location, measurement, and three-dimensional reconstruction of concealed cracks based on GPR images. However, this CNN system could only distinguish concealed cracks from other types of distress, and thus it cannot be regarded strictly as defect recognition. Therefore, in the present study, we developed an application where we combined CNN with GPR images for defect detection in order to obtain highly accurate detection results based on an efficient detection procedure.

In this study, we aimed to employ CNNs to obtain appropriate models for automatically classifying subgrade defects using GPR images of asphalt pavements. The main advantages of the proposed CNN-based method are that it exhibits good stability with different transmitting frequency (300, 500, and 900 MHz), highway structures (five highways with different structures in Zhejiang Province, China), and various type of GPR noise (e.g., foreground and background). The remainder of this paper is organized as follows. In Section 2, we summarize the main approaches employed in this study, including the methods used for generating datasets for CNNs, building the CNN structures, training and testing the CNNs, and analyzing the stability and performance of the CNNs. The performance of the CNNs is discussed in Section 3, including the training and testing performance, stability analysis, and comparative studies. In Section 4, we present an application of a well-developed CNN in Zhejiang, China. We give our conclusions in Section 5.

2. Research approaches

Fig. 1 shows the main research procedure followed in this study. A collection method that employed an air-coupled GPR and a method for confirming different types of defects using core samples were utilized to prepare the datasets for our CNNs. Two CNNs were developed with different architectures based on GPR datasets to recognize subgrade defects. Fig. 2 shows the general developmental flow for the two CNNs. The two CNNs were implemented based on Caffe with an Intel (R) Core (TM) i7-6700 CPU, 8.00 GB random access memory (RAM), and an Nvidia GeForce GTX 1060 6 GB GPU.

2.1. Generating datasets for CNNs

The first step in the development of CNNs for recognizing subgrade defects was the generation of datasets. The complete dataset included training samples, testing samples, and their corresponding target samples.

A high-quality GPR dataset of subgrade defects was required to establish CNN models. The quality of a GPR dataset is often influenced by the acquisition equipment and pavement structures. An air-coupled GPR called OKO GPR was employed to capture GPR images. Three shielding antennae were utilized with 300, 500, and 900 MHz high-frequency electromagnet waves, where their vertical resolution ranges were 0.30–0.47 cm, 0.15–0.27 cm, and 0.09–0.13 cm, respectively. The vertical resolutions of the three shielding antennae met the engineering requirements [31]. The time sampling rate was 1024 scans/s and the distance sampling rate was 10 samples/cm. The height of the air-coupled antenna to the ground is 0.2 m.

A key factor that affects the image quality is the collection method employed, where the optimal collection method should consider both efficiency and precision. Detailed information about