Classifying and Detecting Common Pavement Distresses using Convolutional Neural Network

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Abstract

Allocating fund for maintenance or rehabilitation of road surface is prioritized and carried out through management strategies which are based on pavement rating systems. These rating systems are used by transportation engineers and experts in order for quantifying pavement performance with time. Type, extent, and severity of pavement distresses are considered as important parameters for pavement rating system and its condition evaluation practice. Both asphalt and Portland-cement concrete pavement rating systems like Pavement Condition Rating (PCR) or similar systems include the visual inspection which is time-consuming and expensive. In most instances, distress measurement is subjective, which affects the actual rating. Enhanced collection strategy and data processing technique are necessary to expedite pavement evaluation practice which is the main input for pavement management systems. Recent advances in computer sciences can be applied for identifying and quantifying of pavement distress types through measuring severity, length, width or area by automatic analyses of images captured by a high-resolution camera attached to a drone. In this paper, a cost-effective hardware system is developed for capturing images of pavement surface in order to identify, classify and quantify the common pavement distress types in terms of severity and extent. When the pavement surface is inspected and the distress data is collected by the hardware system which is a drone-mounted camera, the software system, trained and programmed specifically for pavement rating system, is able to obtain a quantitative evaluation of pavement conditions. We have developed an algorithm to images with cracks and without cracks. For that, we used Deep Learning techniques to learn features of images and trained Deep Convolutional Neural Network(CNN) for classification.

[1] [2]

1 Introduction

Applying remote sensing into highway and transportation engineering practices has long been recognized by the United States (US) National Research Council (Council 2006). Recently, transportation agencies nationwide incorporate remote sensing approaches into their standard specification for pavement management system (Schnebele, Tanyu et al. 2015). Moreover, the incorporation of geospatial techniques in pavement assessment is an advancing research area (Olsen, Raugust et al. 2013). But, civil engineers mostly do not have knowledge or background in remote sensing application in geotechnical and transportation engineering (Maas and Hampel 2006, Zeni, Picarelli et al. 2015). As such, this research serves as a link between remote sensing and transportation engineering through being as a reference as well as an approach to develop interdisciplinary studies and collaborations. Since remote sensing serves as a precise and fast technique to collect data, it is considered as an efficient

[1] GEOG 8590: Directed Study(2019)

[2] The code of this project is available at https://github.com/dvlbhanderi/Pavement-Classification-using-CNN

approach for pavement condition assessment.

Transportation agencies utilize the rating systems such as PCI (Pavement Condition Index) in order to evaluate pavement performance and serviceability (Shahin 1982). These rating systems are obtained by visually assessing pavement deteriorations based upon the standard procedures considering the type, severity and density of observed distresses (Hajek, Phang et al. 1986). Since the United States has an extensive road networks, it is not feasible to utilize the traditional techniques to collect data from all present pavement surfaces. Remote sensing is capable of being an efficient alternative or complement to the present traditional methods for pavement surface evaluation (Herold, Roberts et al. 2004, Zhang 2008). United States possesses over 6,000,000 km of roads, and accomplishing a comprehensive pavement assessment through the traditional method has some difficulties including time (closing roads over visual inspections), traffic flow (hazardous for field inspection crew), cost (a large number of trained and experienced engineers)(Schnebele, Tanyu et al. 2015).

Remote sensing also provides an alternative for pavement surface evaluation in high spatial and temporal resolutions (Schnebele, Tanyu et al. 2015). Various sensors and different platforms like moving vehicles and unmanned aerial vehicles (UAVs) are used for identification or the measurement of the pavement surface and subsurface defects (Brecher, Noronha et al. 2004, Koch, Jog et al. 2012). The application of remote sensing into transportation engineering is considered as an important and economically advantageous field of research.

We are living in an booming era of artificial intelligence(AI). The most dazzling sector of AI – Deep Learning – has made substantial breakthroughs in a wide spectrum of fields, ranging from computer vision, speech recognition, natural language processing to robotics. Benefited from these breakthroughs, a set of intelligent applications, as exemplified by intelligent person assistants, video surveillance and personalized recommendations have quickly ascended to the spotlight and gained enormous popularity. It is widely reorganized that these intelligent applications are significantly enriching people's lifestyle and improving human productivity.

For that, we decided to leverage the computer vision techniques to identify the types and severity of the cracks on the roads. Object detection, image classification and semantic segmentation are few of the areas of computer vision that are maturing very rapidly. Due to the lack of data, we decided the scope of the project to image classification only – with cracks and without cracks.

2 Data and Methods

In this paper, three common pavement defects(Figure 1) such as fatigue (alligator) cracking, longitudinal cracking and raveling are investigated. Fatigue cracking occurs due to heavy traffic loadings and generally take places along the vehicle wheel path. This defect is also referred to as alligator cracking because it tends to be similar to the skin pattern of the alligators. The initiation of alligator cracking is detected from observations of fine parallel longitudinal cracks along the wheel-paths. The other common defect of pavement surface is raveling which is the result of traffic abrasive action, asphalt binder weathering, and poor drainage system. This defect is indicated by a progressively separation of asphalt binder and aggregates within the surface asphalt pavement layer. Two sampling roads in Athens-Georgia/United States were selected for the flight surgery at two different altitudes of 10 and 20m. The flight missions were performed on October 23rd and 24th, 2019 at 11am to 1pm. The RGB camera mounted on DJI Phantom 4Pro is used as the only sensor for capturing photographs of road surface defects.

For image classification, with the feeding of a large amount of training samples, the Convolutional Neural Network(CNN) is trained to learn how to recognize an image, and then inference takes real-world images

Figure 1: The pavement defects captured by RGB camera mounted on the drone platform.

as inputs and quickly draws the classifications/predictions of them. CNN or ConvNets are the basic building blocks for most of the computer vision tasks in deep learning era.

As the first CNN to win the ImageNet Challenge in 2012, Krizhevsky and Hinton's AlexNet consists of 5 convolutional layers and 3 fully-connected layers and output layer. The general structure of convolutional neural network with description is shown Figure 2. Our model is based on that. We cut off the last 2 layers and re-used the previous 6 layers to extract features from images. And training a deep neural network needs much experience, data and skill, and it is very time consuming. To overcome that, we re-used the pre-trained network of Krizhevsky.

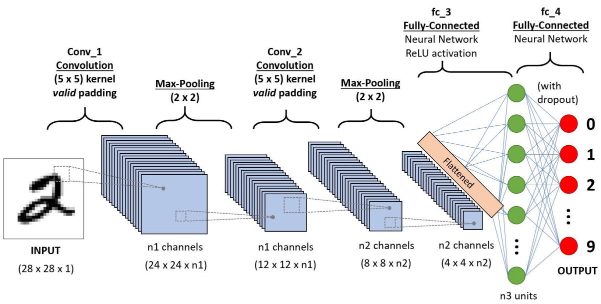

Figure 2: Architecture of Learning task in CNN

The CNN was trained in parallel by two GPUs, and the figures explicitly shows the delineation of responsibilities between two GPUs. First, input images are normalized into 300 $\times$ 300; then the first convolutional layer filters the $300 \times 300 \times 3$ input image with 64 kernels of size of size $11 \times 11 \times 3$ with the stride of 3 pixels. The second convolutional layer takes as input the pooled output of the first convolutional layer and filters it with 256 kernels of size $3 \times 3 \times 32$. The third, fourth and fifth convolutional layers are connected to one another without any intervening pooling layers. The third convolutional layers has 128 kernels of size $3 \times 3 \times 64$, and fourth convolutional layer has 256 kernels of size $3 \times 3 \times 64$. The fully-connected layers have 4096 neurons. Until now, the 5 layer CNN transforms an image into a feature vector of 4096 dimensions. The output of final layer is sent to Softmax layer which converts the numbers between 0 and 1, giving probability of image being of related label. We minimize our loss so as to make the prediction from this last layer as close to actual values. After that, we applied the learned models to classify the test set and evaluated their performance.

3 Results

We trained our network with 50 epoch and just 24 training images. In this method, we finally got the best accuracy 91.67% from CNN classifier with bottleneck features, which is impressive. Features learned by deep neural networks are hierarchical. With more hidden layers, the learned features become more high level and specific. Compared to human-crafted features such as Dense-SIFT or color features, they are more expressive, class-specific, and invariant to backgrounds. Also, we can figure out which layers are critical to recognition and change the parameters and architecture of deep neural network – for example, increase the number of feature maps in some layers, to achieve better performance.

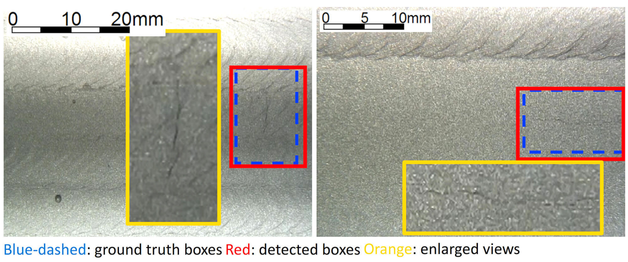

Figure 3: The pavement defects detected by classifier.

To know the remaining problems and achieve better performance, we investigated what kind of images were incorrectly classified. Below figures some characteristics of images that have been failed to classify. Some images' quality are too low to recognize, and some images' critical characters. Moreover, some images even can't be recognized by humans.

Figure 4: Images classified incorrectly.

From the properties of images that failed to classify correctly like as shown in Figure 3, we can try different strategies. We may try object detection and localization to locate the cracks in the roads. But we will need huge data for that. We also can take advantage of extra training set to improve the ability of classification for more complicated images.

4 Conclusion

For view-invariant problems, such as detecting and classifying cracks on road, deep convolutional networks with their stacked internal representation of the input space share many similarities with biological vision.

In this project, we collected data in the form of RGB images of common pavement distresses on roads. Specifically, we first review the background and motivation for artificial intelligence for real world conditions like pavement detection. We then provide an overview of emerging key technology and overarching architecture for deep learning model towards training and inference. We implemented a trainable model that applies CNN to learn features. We also looked insight into what Deep Networks learned from the images. The highest accuracy that we got with CNN is 91.67%.

In the future, we will explore more to achieve better accuracy as well as scope of the project. We also will consider further evaluations across a wider range of datasets to determine if convolutional neural networks consistently offer a significant performance advantage on real-time detection.

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References

Brecher, A., et al. (2004). UAV2003: a roadmap for deploying unmanned aerial vehicle (UAVs) in transportation. Findings of Specialist Workshop in Santa Barbara, CA, December 2003.

A. Krizhevsky, I. Sutskever, G. Hinton (2012). ImageNet Classification with Deep Convolutional Neural Networks. NIPS 2012.

A. Narayan, E. Tuci, M. Alkilabi, F. Labrosse. Road detection using Convolutional Neural Network.

Council, N. R. (2006). Geological and geotechnical engineering in the new millennium: opportunities for research and technological innovation, National Academies Press.

Hajek, J. J., et al. (1986). "Pavement Condition Index (PCI) for Flexible Pavements."

Herold, M., et al. (2004). Road condition mapping with hyperspectral remote sensing.

Airborne Earth Science Workshop.

Koch, C., et al. (2012). "Automated pothole distress assessment using asphalt pavement video data." Journal of Computing in Civil Engineering 27(4): 370-378.

B. Liu, Y. Liu, K. Zhou. Image Classification for Dogs and Cats

Maas, H.-G. and U. Hampel (2006). "Photogrammetric techniques in civil engineering material testing and structure monitoring." Photogrammetric Engineering and Remote Sensing 72(1): 39-45.

Olsen, M. J., et al. (2013). Use of Advanced Geospatial Data, Tools, Technologies, and Information in Department of Transportation Projects, Transportation Research Board.

Schnebele, E., et al. (2015). "Review of remote sensing methodologies for pavement management and assessment." European Transport Research Review 7(2): 7.

Shahin, M. Y. (1982). Airfield pavement distress measurement and use in pavement management.

Zeni, L., et al. (2015). "Brillouin optical time-domain analysis for geotechnical monitoring." Rock Mechanics and Geotechnical Engineering 7(4): 458-462.

Zhang, C. (2008). "An UAV-based photogrammetric mapping system for road condition assessment." Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci 37: 627-632.