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Automatic recognition of asphalt pavement cracks using metaheuristic optimized edge detection algorithms and convolution neural network

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ABSTRACT

Crack detection is a crucial task in periodic pavement survey. This study establishes and compares the performance of two intelligent approaches for automatic recognition of pavement cracks. The first model relies on edge detection approaches of the Sobel and Canny algorithms. Since the implementation of the two edge detectors require the setting of threshold values, Differential Flower Pollination, as a metaheuristic, is employed to fine-tune the model parameters. The second model is constructed by the implementation of the Convolution Neural Network (CNN) – a deep learning algorithm. CNN has the advantage of performing the feature extraction and the prediction of crack/non-crack condition in an integrated and fully automated manner. Experimental results show that the model based on CNN achieves a good prediction performance of Classification Accuracy Rate (CAR) = 92.08%. This performance is significantly better than the method based on the edge detection algorithms (CAR = 79.99%). Accordingly, the proposed CNN based crack detection model is a promising alternative to support transportation agencies in the task of periodic pavement inspection.

1. Introduction

Roads are crucial infrastructures that often suffer from distresses due to their intensive usage. The degradation of pavement condition, especially in developing countries, leads to inferior service quality of transportation networks. This situation currently becomes a phenomenon observed worldwide. For instance, in the United States, 32% of the main roads are in poor or mediocre condition [18]. Needless to say, maintaining roads in a good service condition is very important to safe driving and to economic/social development purposes [22]. To do so, periodic surveys are necessary to provide the collection of data about pavement surface condition. Based on the collected data, important decisions are made regarding the appropriate techniques to be employed in pavement rehabilitation.

In developing countries, human visual inspection is the main method for conducting periodic road pavement surveys. Although this method can provide relatively accurate inspection results, it is notorious for low productivity in both data collection and processing phases. Usually, one inspector can only survey less than 10 km per day due to time-consuming processes of manual data recording and analyses [22]. In addition, manual inspection is also highly prone to subjective judgment. Analysis results on the condition of one road section obtained from two inspectors are very likely to be inconsistent.

Moreover, detecting cracks on the pavement surface is a central task in periodic surveys because cracks are generally the most prevalent type of road distresses and they are characterized by observable texture patterns. As pointed out by Gavilán, et al. [9], cracking on asphalt pavement surface is brought about by vehicle overload, hostile climatic/environment conditions, and structure aging. This phenomenon is an indicator of pavement deterioration and may lead to reduction in design life of the structure if not handled timely [11,18]. Accordingly, timely information regarding asphalt pavement cracks is very useful to pavement maintenance [18]. As stated by Gavilán, et al. [9] and Ouma and Hahn [23], if maintenance tasks are performed in time, the cost for pavement rehabilitation can be saved by up to 80%.

Based on the aforementioned reasons, it is very desirable for transportation agencies that the process of crack detection during road surface survey can be performed automatically. In addition, recent advancements in computer vision and artificial intelligence have presented viable tools for automating the pavement crack detection. Nevertheless, this task is challenging due to the inhomogeneity of crack intensity and complexity of the pavement background [42]. Thus, during the last decade, various intelligent approaches have been proposed to overcome such challenges and attained automatic recognition

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of pavement cracks based on digital images [33,40,41].

Cheng, et al. [5], Wang and Tang [34], and Ying and Salari [39] attempted to construct models for pavement crack analysis based on image thresholding approaches. In these works, various algorithms of image thresholding were utilized in combination with noise removal methods to identify cracks by determining global as well local thresholds of gray level. The accuracy of these image thresholding based models are often limited by the complex texture and shading condition of the digital images. Intelligent models based on edge detection algorithms have been proposed to recognize edges of cracks on pavement surface cracks [1,7,25,31] and obtained promising results.

Models that combined image processing and artificial intelligence algorithms have also been investigated and attained notable improvement in accuracy [6,15]. Nishikawa, et al. [21] established a crack detection model that is based on the technique of iterative image filtering and genetic programming. Cubero-Fernandez, et al. [7] employed the projective integral, which is commonly utilized in the field of face recognition, to extract useful features of crack patterns from pavement images. Mokhtari, et al. [20] carried out a comparative study on the performance of several machine learning models in the task of classifying pavement image samples into 'Crack' and 'No Crack' classes; the research finding is that artificial neural network (ANN) obtained good predictive performance. The performance of ANN is superior to decision tree and *k*-nearest neighbors. Nevertheless, classification models based on those conventional machine learning methods such as ANN and decision tree require a proper extraction and selection of features distilled from digital images. The feature extraction is context dependent and necessitates domain knowledge of both image processing and pavement engineering.

In addition, achieving an accurate model of pavement crack detection using digital images is still in progress within the research community. Image based crack detection is very challenging due to various difficulties including low contrast between the crack objects and the pavement background, the diversity of crack patterns, and the inhomogeneity of gray intensity within one crack object [18]. As stated by Radopoulou and Brilakis [26], automation of crack detection in the real world circumstance needs to be improved. Hence, other alternatives should be investigated to enhance the performance of the task of interest.

In recent years, the arrival and advance of deep learning provides a new and promising solution for constructing automatic pavement crack detection models [8,11,24,32,35,41]. Different from traditional artificial intelligent methods which require that the features of image are specified by human, deep learning allows an integration of feature extraction and image classification processes [10]. Notably, these two processes are both performed autonomously by the machine through the training phase. Convolutional Neural Network (CNN) is an artificial intelligence method that employed the concept and methods of deep learning [17]. A CNN model is capable of learning representations of pavement images with hierarchical levels of abstraction.

Cha, et al. [4] applied CNN in recognizing cracks on surface of concrete structures. The performance of the proposed CNN was compared with traditional Canny and Sobel edge detection methods. The constructed CNN demonstrated a superior performance over the conventional algorithms. However, the tuning parameters of the Canny and Sobel edge detection methods were not optimized.

Zhang, et al. [42] established a road crack detection model based on CNN. However, the performance of the CNN model was not compared with the conventional Canny and Sobel methods. This study also reported promising classification accuracy of CNN. However, this work did not include the details of the CNN model construction process including the backpropagation algorithm and the convergence rates of the CNN model. After the training process, the visualization of filter responses of the CNN model in each convolution layer was not reported. Moreover, the utilization of the trained CNN in recognizing crack objects in testing images larger than the images in the training set was not investigated.

With the aforementioned limitations of previous works in the literature, there is an urging to investigate the performance of CNN and to compare the classification of this deep learning method with conventional approaches including the Canny and Sobel algorithms. With such motivations, the aim of the current research work is to construct two pavement crack detection models. One model is based on the relatively new method of CNN; the other is relied on the conventional edge detection methods of Canny and Sobel algorithms. A data set of 400 image samples has been established to train the two models. Performance of the deep learning model is compared with that of the edge detector. In addition, since the implementation of the edge detectors requires the setting of several threshold values, the Differential Flower Pollination, a metaheuristic algorithm, is employed to optimize the Canny and Sobel algorithms. The rest of the paper is organized as follows: The research method is presented in the second section. The constructed models for automatic crack detection are described in the next section, followed by the section of experimental results. The final section concludes this study with several notes.

2. Research method

2.1. Edge detection algorithms

2.1.1. Sobel algorithm

In image processing field, the Sobel edge detector [27] is a commonly employed approach for image analysis. This algorithm recognizes edges in an image by smoothing the image before computing the derivatives, in the direction perpendicular to the derivative. The following filter is used for smoothing the image before computing the partial derivative in the x direction:

$$h_x = \begin{bmatrix} 1 & 1 \\ 2 & 2 \\ 1 & 1 \end{bmatrix} \tag{1}$$

Since the convolution and the smoothing operators are both linear, they can be combined as following:

$$h_{Sobel,x} = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \tag{2}$$

Similarly, the filter that computes the partial derivative in the y direction is given by:

$$h_{Sobel,y} = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \tag{3}$$

At each point in the image, the resulting gradient approximations can be combined to give the gradient magnitude, using the following equation:

$$h_{Sobel} = \sqrt{{h_{Sobel,x}}^2 + {h_{Sobel,y}}^2} \tag{4}$$

The edge detected image can be obtained from the Sobel gradient with the use of a threshold value T_s. If the Sobel gradient values of pixels in the image are lesser than the threshold value, they are replaced by these threshold values [2].

2.1.2. Canny algorithm

The Canny method [3] is a multi-step algorithm that can detect edges and concurrently suppress noise in the image. At first, a Gaussian filter is employed to smooth the image for removing noise and redundant details or textures of the image background:

$$g(m,n) = G_\sigma(m,n)*\mathrm{f(m,n)} \tag{5}$$

where