

Crack Detection and Classification using Digital Image Processing

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Certificate of Original Authorship

I, Thi Hong Nhung Nguyen declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Electrical and Data Engineering/Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of the requirements for a degree at any other academic institution except as fully acknowledged within the text. This thesis is the result of a Collaborative Doctoral Research Degree program with The VNU University of Engineering and Technology (VNU-UET).

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Abstract

Crack detection and segmentation, and the processes of crack classification and crack index calculation which they support, are essential tools in road survey and maintenance applications. The outputs of crack detection and segmentation are used to define the severity levels of the cracking of road surfaces. Based on the crack severity levels, necessary repair and maintenance can be decided.

There are many image processing methods that may be applied to this domain, including traditional methods using low-level features such as edges, and modern methods using machine learning algorithms such as deep learning which are able to abstract high-level features. However, many challenges associated with the use of digital image processing to detect and segment cracks in images are still not solved. Some of these challenges and limitations include: (1) crack images are often noisy, have low-resolution, and contain many artifacts; (2) the associated road crack datasets are imbalanced, with only a small proportion of the data representing crack information; (3) three dimensional (3D) data such as crack point clouds are informative to analyze and monitor the development of crack but current acquisition methods for this data produce low-density point clouds and this problem needs to be addressed to make these data sets more useful; (4) the automated calculation of crack indices is frustrated by the lack of robust, standardised methods for automatically identifying cracks and measuring crack parameters such as crack length and crack width.

To solve the above limitations, this thesis focuses on three main contributions:

The first contribution is the proposal of a new architecture for crack detection and segmentation. This method improves the ability to segment the crack from noisy and imbalanced road crack datasets. A combination of crack detection at the region (or sample) level and crack segmentation at the pixel level is shown to increase the accuracy of crack segmentation.

In the second contribution, a novel method of crack point cloud upsampling is proposed. By combining the point clouds and their corresponding 2D images in a model based on a GAN (Generative Adversarial Network) framework, the proposed method aims to generate high-resolution point clouds from low-resolution point clouds and matched 2D images. The high-resolution point clouds can be used to improve the classification of crack point clouds and support crack monitoring.

The final contribution is a method to calculate crack parameters such as crack length and crack width from segmented cracks. This contribution proposes an approach for evaluating the crack length results based on the traditional metric Precision Recall Curve (PRC). The new approach is suitable for a range of narrow features such as crack lines.

This thesis shows the impressive power of using digital image processing and machine learning for crack analysis in both 2D or 3D crack data.

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