

UNIVERSITY OF TECHNOLOGY SYDNEY
Faculty of Engineering and Information Technology

**Summit Navigator for Local Maxima Extraction
with Surface Inspection Applications**

by

Tran Hiep Dinh

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Certificate of original authorship

I, Tran Hiep Dinh declare that this thesis, is submitted in fulfilment of the requirements for the award of the 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. This document has not been submitted for qualifications at any other academic institution.

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Abstract

Machine vision offers an excellent tool for critical real-world inspection in industrial applications. In an automated vision-based system, image processing and, in particular, image segmentation remain an essential task, for which automatic extraction of local maxima is an important process not only to extract the foreground for post processing but also to separate objects from the background for identification and classification. Addressing this topic, the current thesis presents two algorithms. First, a novel peak detection algorithm, the Summit Navigator, is developed to detect true peaks from gray-scale histograms of images. Here, inspired by experience of mountain explorers in strategic planning, two location-based parameters, namely the offset distance and observability index, are formulated to search for all possible dominant peaks. Notably, this approach does not require any a priori knowledge of the number of modes or distance between the modes in process. The false positives of the searching phase are recursively filtered by means of unimodal and linear fitting. Experiments on time series data and natural images are conducted to demonstrate the advantages of the proposed algorithm in terms of accuracy and consistency. Second, a binarised version of Summit Navigator is proposed for detection of possible defects in built infrastructure. Based on the initial segmentation of Summit Navigator, a new binarisation algorithm is proposed for surface inspection by extracting potential defect information from the background of gray-scale images. To incorporate the idea of multi-level thresholding into a binarisation solution, a contrast-based region merging technique is developed. This approach is based on the observation that the defect-like regions notably appear darker than the surrounding areas. Hence, recursively combining regions with similar intensity can result in two most distinguished areas in terms of contrast difference. A data processing scheme is introduced to extract training data from some reputable image

database. Then, the Bootstrap Aggregation (Bagging) technique is employed using the decision trees method to train a classification model for automatic parameter selection. Two unmanned systems are also put forward to support the data collection and the feasibility validation of the method in surface inspection. Experiments on natural image binarisation and defect detection tasks are carried out to evaluate the effectiveness of the proposed algorithm over state-of-the-art techniques.

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School of Electrical and Data Engineering