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OPTIMIZED TECHNIQUES FOR LANDSLIDE DETECTION AND CHARACTERISTICS USING LiDAR DATA

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By

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Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

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Chairman : Professor Biswajeet Pradhan, PhD
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Landslides are one of the major natural disasters that cause severe damage to lives and properties worldwide. Historically, landslide occurrences are usually mapped by taking inventory of location and magnitude of the landslide in a region. This information is used to examine and manage slope failures and distributions effectively. A good landslide inventory map is a prerequisite for analyzing landslide susceptibility, hazard, and risk. Field survey, optical remote sensing, and synthetic aperture radar techniques are traditional techniques use for landslide detection in tropical regions. However, such techniques are time consuming and costly. In addition, the dense vegetation in tropical forests affects the accuracy of the landslide inventory maps. Furthermore, it is difficult to distinguish different types of landslides due to geomorphological development along hillsides using the traditional approach. so, it necessary to develop more innovative approach that can resolve the aforementioned challenges.

Therefore, in line with the objectives of this research, very- high-resolution LiDAR point cloud data and orthophotos image, have been utilized to map the landslide events in Cameron Highlands, Malaysia. The segmentation process was optimized using Fuzzy-based Segmentation Parameter. Also, six techniques: Ant Colony Optimization (ACO), Gain Ratio (GR), Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), Random forest (RF), and Correlation-based Feature Selection (CFS) were used for the feature selection. The locations of landslides were detected accurately by employing two Machine learning classifiers, namely, SVM and RF, decision rule and hierarchal rules sets were developed by applying decision tree (DT) algorithm to provide improved landslide inventory. In this task, two neural network algorithms, Recurrent Neural Networks (RNN) and Multi-Layer Perceptron Neural Networks

(MLP-NN) were used and the hyper-parameters of the network architecture was optimized based on a systematic grid search.

The performance of the outcome was validated based on the receiver operating characteristic (ROC) area under the curve (AUC) values, confusion matrix and Cross Validation method. Transferability of each of the models was verified by testing in another site for consistency. The overall accuracy of the Support Vector Machine SVM and Random Forest RF classifiers revealed that three of the six algorithms exhibited higher ranks in the landslide detection. The classification accuracy of the RF classifier is observed to be higher than that of SVM using either all features or only the optimal features. The proposed techniques performed well in detecting landslides in tropical area in Malaysia. Furthermore, the transferability indicates that the techniques can easily be extended to any region with similar characteristics.

The result show that the accuracy of shallow and deep-seated landslides were 0.80 and 0.83, respectively. The intensity derived from the LiDAR data, geometric and texture features significantly affects the accuracy of differentiating shallow from deep-seated landslides. While, the results of shallow and deep using hierarchal rules set were observed to be 87.2%, and 90% respectively, for site A (Analysis area). More so, the hierarchal rules set were evaluated using another site named site B (Test area), and the accuracies of shallow and deep seated were found to be 86.4% and 80.8% respectively. This indicates that LiDAR data are highly efficient in detecting landslide characteristics in tropical forested areas.

Furthermore, RNN and MLP-NN models in the test area showed 81.11%, and 74.56%, accuracy level, respectively. These results indicated that the proposed models with optimized hyper-parameters produced the accurate classification results. The LiDAR-derived data, orthophotos and textural features significantly affected the classification results. The results indicated that the proposed methods have the potential to produce accurate and appropriate landslide inventory in tropical regions such as Malaysia. Hopefully, this innovative method can be deployed in detecting landslide and distinguish between different types of landslides (shallow and deep-seated landslides) in the near future for landslide management due to its transferability capabilities to different environments.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PEMBANGUNAN TEKNIK YANG DIKENAKAN UNTUK PENGESANAN TANAH RUNTUH DAN SIFAT DARI PEMANTAUAN DATA DARI LASER UDARA DAN ORTHOFOTO

Oleh

MUSTAFA RIDHA MEZAAL

Mei 2018

Pengerusi : Profesor Biswajeet Pradhan, PhD
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Tanah Tanah runtuh merupakan salah satu bencana alam yang boleh mengakibatkan kemalangan jiwa dan kerosakan harta benda. Menurut sejarah, kejadian tanah runtuh kebiasaannya dikesan dengan mengenal pasti lokasi dan magnitud kejadian tanah runtuh tersebut di sesuatu kawasan dan maklumat ini digunakan untuk mengkaji corak tebaran tanah runtuh bagi menguruskan hakisan tanah dengan berkesan. Peta kajian tanah runtuh yang baik merupakan satu keperluan penting bagi mengenal pasti kawasan yang terdedah dan berisiko untuk berlakunya tanah runtuh selain daripada untuk mengkaji perubahan landskap yang berlaku akibat daripada kejadian tanah runtuh. Pengukuran tanah, sensor penderiaan jauh dan teknik sintetik bukaan radar adalah antara teknik tradisional untuk mengenal pasti tanah runtuh di kawasan tropika. Walaubagaimanapun, teknik-teknik traditional ini adalah lambat dan menelan kos yang sangat besar. Tambahan pula, ketebalan tumbuhan hutan tropika merumitkan penghasilan peta kajian tanah runtuh di kawasan ini dengan lebih berkesan. Teknik-teknik traditional ini bukan sahaja lambat bahkan sukar untuk membezakan jenis-jenis kejadian tanah runtuh kerana pembangunan geomorfologi di kawasan persisiran bukit dan pergerakan tektonik dalam tanah itu sendiri.

Hasil kajian ini membentangkan beberapa kaedah untuk mengesan tanah runtuh dan keupayaan bagi membezakan antara tanah runtuh yang cetek dan dalam dengan menggunakan pengesan cahaya dan berbagai-bagai set data-LiDar dan kepenggunaannya mengikut keadaan persekitaran yang berbeza. Antara objektif khusus kajian ini adalah: 1) mengenal pasti algoritma yang sesuai untuk pemilihan ciri bagi menambah baik proses mengesan tanah runtuh, 2) untuk mengoptimumkan ketetapan peraturan keputusan data set dan hierarki peraturan untuk membezakan ciri-

ciri kegelongsoran yang berlainan, 3) untuk membangunkan prosedur pembelajaran (Seni Bina Saraf) bagi pemetaan tanah runtuh. Bagi mencapai matlamat ini, pertama, proses segmentasi dioptimumkan dengan menggunakan selia logik kabur. Selepas itu, enam teknik: Pengoptimuman Koloni Semut (ACO), Nisbah Perolehan (GR), Pengoptimuman Kawanan Zarah (PSO) dan Algoritma Genetik (GA), Hutan Rawak (RF), dan Hubungan Pemilihan Ciri (CFS) telah digunakan untuk pemilihan ciri. Di sini, lokasi tanah runtuh telah dikesan dengan tepat dengan menggunakan dua teknik mesin pengasingan pembelajaran, iaitu, MSV dan HR. Di samping itu, peraturan keputusan dan peraturan set hierarki telah dibangunkan dengan menggunakan Pohon Keputusan (DT) algoritma untuk menyediakan inventori tanah runtuh yang lebih baik. Dalam tugas ini, dua rangkaian neural algoritma telah digunakan iaitu Rangkaian Saraf Berulang (RNN) dan Rangkaian Saraf Pelbagai Lapisan Perceptron (MLP-NN). Dalam proses ini juga, lebihan parameter dari rangkaian seni bina telah dioptimumkan berdasarkan carian grid yang sistematik.

Kesemua prestasi tersebut telah disahkan berdasarkan nilai di bawah kurva (AUC) dalam ciri-ciri operasi penerima (ROC), matriks kekeliruan dan pengesahan silang. Setiap pemindahan model telah disahkan dengan diguna pakai di kawasan lain. Untuk objektif pertama, keseluruhan ketepatan daripada Mesin Sokongan Vektor (SVM) dan pengelas Hutan Rawak (RF) mendedahkan bahawa tiga daripada enam algoritma berjaya mempamerkan ketepatan yang lebih tinggi dalam mengesan kejadian tanah runtuh. Ketepatan pengelasan bagi pengelas (RF) adalah lebih tinggi daripada pengelas (SVM) walau sama ada dengan menggunakan kesemua ciri atau ciri optimum sahaja. Teknik yang dicadangkan ini adalah yang terbaik dalam mengesan tanah runtuh di kawasan tropika seperti Malaysia. Oleh yang demikian, teknik-teknik ini mudah untuk diguna pakai di mana-mana kawasan yang mempunyai ciri-ciri yang hampir serupa.

Objektif kedua menunjukkan bahawa ketepatan bagi mengenal pasti jenis-jenis tanah runtuh sama ada cetek dan mendalam adalah 0.80 dan 0.83. Keamatan yang diperolehi daripada tekstur dan data LiDAR dengan ketara sangat mempengaruhi ketepatan dalam membezakan tanah runtuh cetek dengan mendalam. Walau bagaimanapun, didapati bahawa keputusan data bagi tanah runtuh cetek dan mendalam dengan menggunakan aturan hierarki adalah 87.2% dan 90.0%., untuk kawasan A (iaitu kawasan yang dianalisis). Sementara itu, set aturan hierarki yang sama diguna pakai di kawasan B (iaitu kawasan yang dikaji), dan ketepatan dalam mengenal pasti tanah runtuh cetek dan mendalam adalah 86.4% dan 80.8%. Oleh yang demikian, hasil kajian ini menunjukkan bahawa data LiDAR adalah sangat berkesan dalam mengesan dan mengenal pasti jenis-jenis tanah runtuh di kawasan hutan hujan tropika.

Selain itu, hasil daripada objektif ketiga pula menunjukkan bahawa ketepatan bagi model RNN dan MLP-NN yang dijalankan di kawasan uji kaji masing-masing adalah 81.11% dan 74.56%. Oleh itu, keputusan ini menunjukkan bahawa model yang dicadangkan dalam kajian ini menghasilkan hasil klasifikasi yang sangat tepat dengan mengoptimumkan beberapa parameter-hiper. Di sini, data daripada LiDAR, orthofotos dan ciri-ciri tekstur amat mempengaruhi hasil klasifikasi kajian.

Keputusan dari hasil kajian ini menunjukkan bahawa kaedah yang dicadangkan berpotensi untuk menghasilkan inventori jenis tanah runtuh dengan tepat dan sesuai diguna pakai di kawasan hutan hujan tropika seperti Malaysia. Algoritma dan maklumat yang diperolehi daripada kajian ini dapat menyumbang kepada pengurusan tanah runtuh di negara-negara hutan hujan tropika.

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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Declaration by Members of Supervisory Committee

This is to confirm that:

- the research conducted and the writing of this thesis was under our supervision;
- supervision responsibilities as stated in the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) were adhered to.

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LIST OF ABBREVIATIONS

ACO	Ant Colony Optimization
AUC	The area under curve
CFS	Correlation-based Feature Selection
DEM	Digital Elevation Model
DNN	Deep Neural Network
CWT	Continuous Wavelet Transform
DSM	Digital surface model
DN	Digital Number
EC	Evolutionary Computation
DT	Decision Tree
RBF	Radial Basis Function
SAR	Synthetic Aperture Radar
GA	Genetic Algorithm
GIS	Geographic information system
GR	Gain ratio
LiDAR	Light Detection and Ranging
MLP	Multi-Layer Perceptron
nDSM	Normalized Digital Surface Model
OBIA	Object-based Image Analysis
PSO	Particle Swarm Optimization
RF	Random Forest
RNN	Recurrent Neural Networks
ROC	Relative Operating Characteristic
RS	Remote Sensing
SPOT	Satellite Pour l'Observation de la Terre
SVM	Support Vector Machine
DM	Data Mining
VHR	Very High Resolution
OOB	"Out-of-Bag
LULC	Land Use /Cover
BPNN	Back-Propagation neural network

PNN	Probability Neural Network
UA	User Accuracy
PA	Producer Accuracy
OA	Overall Accuracy
Cor	Correlation
Stdev	Standard Deviation
GLCM	Gray-Level Co-occurrence Matrix
GLDV	Grey level difference vector
TP	True Positives,
TN	True Negatives
FP	False Positives
FN	False negatives

CHAPTER 1

INTRODUCTION

1.1 Introduction

The rapid expansion of cities and the continuously increasing population in urban areas lead to the establishment of settlements in mountainous areas. This phenomenon has increased the impact of natural disasters, particularly landslides, in these mountainous areas. Landslides result in severe property losses, human casualties, and environmental damage. Landslides are considered one of the geological phenomena – along with earthquakes, subsidence, volcanic activity and glacial rebound – to contribute to ground deformation (Pradhan and Lee, 2010). In the near future, climate change induced by anthropogenic actions such as urban expansion and deforestation, will lead to higher landslide occurrences. Considering the wide coverage of landslide damages, planners and decision makers have to identify location of landslide to mitigate the event (Pradhan et al., 2011). Two major aspects should be considered to produce an efficient landslide inventory map. One aspect is related to the data used, whereas the other is related to the methods employed (Pradhan et al., 2016).

Landslides are geological disasters with catastrophic effects on human lives and properties. Landslide incidence is related to a cluster of triggering factors, such as intense rainfall, volcanic eruptions, rapid snowmelt, elevated water levels, and earthquakes (Tehrany et al., 2014a). Landslide inventory maps are required for various purposes such as: (i) recording the magnitude of landslide in a region, (ii) performing the initial steps in analysing the susceptibility, hazard, and risk of the landslide (Van Westen et al., 2008; Guzzetti et al., 2012; Althuwaynee et al., 2014a; Althuwaynee et al., 2014b; Pradhan et al., 2016), and (iii) examining the patterns of landslide distributions and studying the evolution of landscape affected by landslides (Parker et al., 2011; Pradhan et al., 2016). Mapping of landslide susceptibility, hazards, and risks is imperative to achieve the mitigation planning (Pradhan and Buchroithner, 2010). The identification and mitigation of landslide occurrences are also crucial within the field of hazard management and mitigation research (Guzzetti et al., 2012).

According to Metternicht et al. (2005), remote sensing (RS) technology provides detail information about landslides for policy-makers and emergency managers. Selecting relevant features is important for distinguishing between landslides and non-landslides as well as classifying landslides (Van Westen et al., 2008). Mapping a landslide inventory in tropical areas is challenging because the dense vegetation cover in these regions obscures underlying landforms (Chen et al., 2015). The precision of derived maps depends not only on the methodology adopted but also on the quality of the features selection. The use of a large number of features can decrease the accuracy of landslide detection because of the presence of irrelevant features (Stumpf and Kerle, 2011). Moreover, the dense vegetation of tropical forests complicates the generation of an accurate landslide inventory map in these regions. Therefore, the present study aims to utilize light detection and ranging (LiDAR) data and orthophoto image along with recent optimized techniques, in detecting landslides and differentiating between their characteristics.

1.2 Problem Statement

Field survey, optical remote sensing, and synthetic aperture radar techniques are traditional techniques use for landslide detection in Remote Sensing and Geographic Information System (GIS) (Pradhan et al., 2016). However, there exist some challenges that affect its accuracy and performance. In a dense vegetation cover, it is difficult to use the traditional technique due to the obstruction from mountains and shadows (Chen et al., 2014). Many researches have attempted to develop rule-set based on time trial-error method. However, the rule-set development with the trial-and-error optimization method is time consuming, and the optimum rulesets are difficult to be determined (Sameen et al., 2017). Also, many investigations have been carried out using hierarchical approach with multiresolution sets of images. However, this approach has not been adopted in differentiating between types of landslide (shallow and deep seated) using LiDAR data. Despite the viability of Neural Architecture techniques in many areas of endeavour such as GIS, the technique has not been deployed with LiDAR data in detecting landslide.

1.3 Motivation Behind this Research

Nowadays, natural hazards are common in today‘s life. Increasing amounts of natural catastrophes have proved to the human the vital importance of the natural hazards issues for the safety of the environment, and the populations. Rapid urbanization and climate change are expected to raise the amount of landslide. Landslide results in sever property losses, human casualties and environmental damage. The dramatic landslides which occur in tropical countries, especially Malaysia, emphasize the extremity in climatic variations. Since large-scale landslides often cause severe damage to human lives and properties, it is desirable to identify and map them for hazard mitigation purposes (Lin et al., 2013a). This phenomenon triggers due to the unexpected variations of the state of features due to natural forces, such as rainfall, and human activities. In most cases, human beings are not capable of controlling and predicting these disasters precisely. When major natural catastrophes such as landslides, earthquakes, floods and land subsidence occur, they have a definite impact upon human lives, belongings, infrastructure, farming and environment. The influence of natural hazards varies based on the intensity and coverage of region.

Landslides are of the most commonly occurring natural catastrophes that influence human beings and their surrounding environment. Inhabitants of Asia and the Pacific regions are affected in terms of social and economic stability. According to Pradhan (2010), high percentage of the destructions related to natural catastrophes in Malaysia are produced by landslide. Furthermore, average annual landslide damage is as high as $10 million USD. The attention towards providing proper landslide management has risen over the last few centuries. The recent reasons for recurrent landslides within some regions are mostly due to unplanned urbanization, construction and deforestation. In spite of these factors, it is possible to predict and mitigate effects of landslides with the use of various technology. The use of technology can facilitate landslide prevention actions to detect the landslide areas and to have an early warning for this catastrophe.

This thesis attempts to propose novel techniques for mapping the landslide in vulnerable locations using state- of-the-art machine learning methods. The key motivation of this research is to establish high-quality landslide inventory maps by applying semi-automatic techniques. To recognize those susceptible regions, landslide inventory maps should be generated as a basis of landslide susceptibility mapping in order to avoid more urbanization in hazardous areas. To reduce the damage and victims in case of a landslide occurrence, it is critical to locate the susceptible areas. Additionally, optimized techniques vastly improve the accuracy of classifications. Governments and planners can utilize the generated results of this study to identify safe regions for inhabitants, support the first ones to respond to emergencies, and update the urban planning strategies. Such data can decrease the requirements for performing field surveys by agencies such as departments of surveying.

1.4 Research Objectives

The present thesis proposes and applies various new methods that clearly contribute to the gap in the literature. These methods are simple, repeatable, and comprehensive. The following are the main objectives of the thesis:

1. To investigate the suitable selection features algorithms in landslide detection.
2. To optimize rule sets to distinguish various landslide characteristics and compare its performance with hierarchical rule-set classification approach.
3. To apply deep learning (Neural Architecture) classifier for landslide mapping.

1.5 Research Questions

This thesis comprehensively addresses the following research questions:

1. What are the results of the selected feature techniques using high resolution LiDAR data? How do the selected relevant features contribute to detection of landslides and differentiation of two landslide types in a highly dense, vegetated area?

2. What is the result of the optimize rule data with high density LiDAR data? How can this be helpful in detecting landslides and differentiating between two types of landslide?
3. How effective is the supervised approach classification method in defining the landslide prone areas?
4. How do the LiDAR derived data aid in differentiation of deep seated and shallow landslides?
5. How does the optimized segmentation aid in delineating the boundary of landslides and improve in its exploitation?
6. How do the decision rule sets aid to distinguish between two types of landslides?
7. How do the hierarchal rules set contribute to differentiation of two types of landslides?
8. How do deep neural networks help in detecting landslides within tropical areas?

1.6 Scope of this Thesis

This study is carried out to develop a method for detecting and distinguish landslide areas using remote sensing and GIS techniques in a tropical environment like Cameron Highland, Malaysia. Also, transferability capability to similar geological and geomorphological areas are investigated and tested in other study areas. In this research, airborne laser scanning techniques is used to detect landslides and to distinguish between shallow and deep-seated landslides. Six (6) algorisms; Ant Colony Optimization (ACO), Gain Ratio (GR), Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), Random forest (RF), and Correlation-based Feature Selection (CFS) are used for the feature selection. The performance of the feature selection algorism is evaluated using two Machine learning classifiers, namely support vector machine (SVM) and random forest (RF). Decision rule and hierarchal rules set are developed by applying decision tree (DT) to provide improved landslide inventory map. In this task, two neural network algorithms, Recurrent Neural Networks (RNN) and Multi-Layer Perceptron Neural Networks (MLP-NN) are used and the hyper-parameters of the network architecture was optimized based on a systematic grid search.

1.7 Research Hypothesis

1. The optimized techniques for both segmentation parameters and feature selection may improve and facilitate the generation of landslide inventory map with high density LiDAR data.

2. Decision rule and hierarchal rule sets along with relevant features may improve significantly in differentiating between the landslide types.

3. Deep neural network may contribute in improving accuracy of a landslide inventory map.

1.8 Thesis Organization

This thesis is organized into five chapters. The summary of each chapter is as follows:

(i) CHAPTER 1: INTRODUCTION

This chapter introduces the problem statement of the study, aim, objectives and scope of the study. Furthermore, this chapter highlights the research questions proposed for the thesis as well as the significant contribution of new knowledge and the overall structure of the thesis.

(ii) CHAPTER 2: LITERATURE REVIEW

This chapter provides an overview of landslide status in various regions and previous work of using remote sensing and GIS to detect landslides. The two types of landslide detection techniques were outlined followed by the traditional and innovative and emerging techniques for detecting landslide prone areas. Next, the methodology used to detect and distinguish landslides using different techniques were discussed. Finally, validation methods used to assess the accuracy of maps produced are summarized.

(iii) CHAPTER 3: MATERIALS AND METHODOLOGY

This chapter details the characteristics of the study area followed by the following details in order: materials, data, methodology, optimized segmentation, evaluation of the training sample, features selection algorithms, detection, differentiation of the types of landslide (i.e. deep seated and shallow), and various remote sensing techniques.

(iv) CHAPTER 4: RESULTS AND DISCUSSION

This chapter focuses on the results of the study, which include the analysis results, optimized segmentation, and selected feature algorithms using LiDAR data – supported by photos, tables, diagram and charts. This chapter also discusses the results of optimized segmentation. Afterwards, decision rule and hierarchal rules were used in differentiating between two types landslides with regards to their characteristics. Lastly, the results of the deep neural network – using only the LiDAR derived data – were employed for detecting landslides and differentiating between the two types of landslides are discussed.

(v) CHAPTER 5: CONCLUSION AND FUTURE WORK RECOMMENDATIONS

This chapter provides the overall conclusion from this study, recommendation and further research for the study area.

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