

UNIVERSITI PUTRA MALAYSIA

MODELING OF ROAD GEOMETRY AND TRAFFIC ACCIDENTS BY HIERARCHICAL OBJECT-BASED AND DEEP LEARNING METHODS USING LASER SCANNING DATA

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

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Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

MODELING OF ROAD GEOMETRY AND TRAFFIC ACCIDENTS BY HIERARCHICAL OBJECT-BASED AND DEEP LEARNING METHODS USING LASER SCANNING DATA

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Road traffic accidents are global concerns since they affect human life, economy, and road transportation systems. Rapid information acquisition and insight discovery are key tasks in transportation management. Specifically, extraction of geometric road features such as slopes and superelevation are essential information to understand the effects of road geometry on road traffic accidents. However, to understand these effects clearly and accurately, proper modeling techniques should be used. This study aims to develop methods to extract geometric road features (e.g., vertical gradients, superelevation, width, design speed) and establish associations between those features and road traffic accidents including frequency and accident severity. There was a need for efficient segmentation algorithm, optimization strategy, feature extraction and classification, and robust statistical and computational intelligence models to accomplish the set aims. Experimental results regarding road geometry extraction indicated that the proposed methods could achieve relatively high accuracy (~ 85% -User's Accuracy) of road detection from airborne laser scanning data. Our method improved the overall accuracy of classification by 7% outperforming the supervised k nearest neighbour method. In addition, the results also showed that the proposed hierarchical classification method could extract geometric road elements with an average error rate of 6.25% for slope parameter and 6.65% for superelevation parameter, and it is transferable to other regions of similar environments. On the other hand, the geometric regression model predicted the number of accidents in the North-South Expressway with a reasonable accuracy ($R^2 = 0.64$). This model also could identify the most influential factors contributing to the number of accidents. Experiments on deep learning models showed that the recurrent neural network performs better than the feedforward neural networks, statistical bayesian logistic regression, and convolutional neural networks. This study also suggests that transfer learning could improve the forecasting accuracy of the injury severity by nearly 10%.



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

PERMODELAN GEOMETRI JALAN DAN KEMALANGAN LALULINTAS DENGAN OBJEK HIRAEKI DAN KAEDAH *DEEP LEARNING* MENGGUNAKAN IMBASAN DATA LASER

Oleh

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Pengerusi : Profesor Biswajeet Pradhan, PhD Fakulti : Kejuruteraan

Kemalangan jalan raya adalah kebimbangan global kerana ia mempengaruhi kehidupan manusia, ekonomi, dan sistem pengangkutan jalan raya. Pemerolehan maklumat yang cepat dan penemuan wawasan adalah tugas utama dalam pengurusan pengangkutan. Khususnya, pengekstrakan ciri-ciri jalan geometri seperti cerun dan penyempurnaan adalah maklumat penting untuk memahami kesan geometri jalan raya pada kemalangan jalan raya. Walau bagaimanapun, untuk memahami kesan-kesan ini dengan jelas dan tepat, teknik pemodelan yang betul harus digunakan. Kajian ini bertujuan untuk membangunkan kaedah untuk mengekstrak ciri-ciri jalan geometri (cth., Kecerunan menegak, superelevasi, lebar, kelajuan reka bentuk) dan mewujudkan persatuan antara ciri-ciri dan kemalangan jalan raya termasuk kekerapan dan keterukan kemalangan. Terdapat keperluan untuk algoritma segmentasi yang berkesan, strategi pengoptimuman, pengekstrakan dan klasifikasi ciri, dan model perisikan statistik dan komputasi yang mantap untuk mencapai matlamat yang ditetapkan. Hasil eksperimen mengenai pengekstrakan geometri jalan menunjukkan bahawa kaedah yang dicadangkan dapat mencapai ketepatan yang agak tinggi (~ 85% - Akurasi Pengguna) pengesanan jalan dari data pengimbasan laser udara. Kaedah kami meningkatkan ketepatan keseluruhan klasifikasi sebanyak 7% yang melebihi kaedah jiran terdekat yang diselia. Di samping itu, keputusan juga menunjukkan bahawa kaedah klasifikasi hierarki yang dicadangkan dapat mengekstrak unsur jalan geometri dengan kadar kesilapan purata 6.25% untuk parameter cerun dan 6.65% untuk parameter superelevasi, dan ia boleh dipindahkan ke kawasan lain yang serupa persekitaran. Sebaliknya, model regresi geometri meramalkan bilangan kemalangan di Lebuhraya Utara-Selatan dengan ketepatan yang munasabah ($R^2 = 0.64$). Model ini juga dapat mengenal pasti faktor-faktor yang paling berpengaruh yang menyumbang kepada bilangan kemalangan. Eksperimen dalam model pembelajaran mendalam menunjukkan bahawa rangkaian neural berulang lebih baik daripada rangkaian saraf feedforward, regresi logistik bayesian statistik, dan rangkaian saraf convolutional. Kajian ini juga menunjukkan bahawa pemindahan pembelajaran dapat meningkatkan ketepatan ramalan keterukan cedera oleh hampir 10%.



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LIST OF ABBREVIATIONS

	LiDAR	Light Detection And Ranging
	ALS	Airborne Laser Scanning
	MLS	Mobile Laser Scanning
	TLS	Terrestrial Laser Scanning
	3D	Three Dimension (s)
	OBIA	Object-Based Image Analysis
	DEM	Digital Elevation Model
	DL	Deep Learning
	2D	Two Dimension (s)
	FOV	Field of View
	RNN	Recurrent Neural Network (s)
	TL	Transfer Learning
	IMU	Inertial Measurement Unit
	DSM	Digital Surface Model
	NN	Neural Network (s)
	UAV	Unmanned Aerial Vehicle (s)
	ACO	Ant Colony Optimization
	SVM	Support Vector Machine (s)
	GNSS	Global Navigation Satellite System
	GIS	Geographic Information System
	GR	Geometric Regression
	GPS	Global Positioning System
	PCA	Principal Component Analysis
	TOF	Time of Flight
	UPM	Universiti Putra Malaysia
	ML	Machine Learning

	LR	Logistic Regression
	CNN	Convolutional Neural Network (s)
	HD	High Definition
	NSE	North-South Expressway
	PSO	Particle Swarm Optimization
	LULC	Land Use and Land Cover
	EA	Evolutionary Algorithm (s)
	RF	Random Forest
	GLONASS	Global Orbiting Navigation Satellite System
	USGS	United States Geological Survey
	DTM	Digital Terrain Model
	МСС	Multiscale Curvature Classification
	EDM	Electronic Distance Measurement
	RMS	Root Mean Square
	PCD	Phase Coded Disk
	DT	Decision Tree
	SPOT	Système Pour l'Observation de la Terre
	MRS	Multi-Resolution Segmentation
	NDVI	Normalized Difference Vegetation Index
	GVF	Gradient Vector Flow
	RANSAC	RANdom SAmple Consensus
	CRF	Conditional Random Field
	CAD	Computer-Aided Design
	ETC	Electronic Toll Collection
	NB	Negative Binomial
	MA	Moving Average
	AR	Autoregressive

	KNN	K-Nearest Neighbors
	MLPNN	Multilayer Perceptron Neural Networks
	RBFNN	Radial Basis Function Neural Networks
	SAP	Smeed Accident Prediction
	SLPNN	Single-Layer Perceptron Neural Network
	GRNN	General Regression Neural Network
	MLR	Multilayer Regression
	GDP	Gross Domestic Product
	MSE	Mean Square Error
	ReLU	Rectified Linear Unit
	GA	Genetic Algorithms
	LSTM	Long Short-Term Memory
	GCPs	Ground Control Points
	PLUS	Projek Lebuhraya Usaha Sama
	VIF	Variance Inflated Factor
	DGPS	Differential Global Positioning System
	AADT	Average Annual Daily Traffic
	BD	Bhattacharyya Distance
	POF	Plateau Objective Function
	SNR	Signal-To-Noise Ratio
	MS	Mean Shift
	UA	User's Accuracy
	ED	Euclidean Distance
	SGD	Stochastic Gradient Descent
	BPTT	Backpropagation Through Time
	OA	Overall Accuracy
	AIC	Akaike Information Criterion

APM	Accident Prediction Model
МСМС	Markov Chain Monte Carlo
BGR	Brooks-Gelman-Rubin
DIC	Deviance Information Criterion
PC	Personal Computer
GPUs	Graphics Processing Units
KIA	Kappa Index of Agreement
BLR	Bayesian Logistic Regression

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CHAPTER 1

INTRODUCTION

1.1 Background of Study

Transportation systems specifically road transport are highly essential to economic activities. They play a vital role in marketing products and providing citizens with ease of access to points of contact for business activities, health, education, and agriculture. Road transportation systems must be safe and efficient to keep the above services active. However, almost every road section has a significant risk of traffic accidentsa primary global concern due to many fatalities and economic losses every year. For example in Malaysia, the recent statistics show that deaths per 100,000 people are nearly 24 for all road users (Global Status Report on Road Safety 2015). Mainly, expressways and highways in urban areas are potential sites of fatal traffic accidents. On an average, 18 people are killed daily nationwide in road accidents as per a survey conducted in 2015. In 2016, the number of fatalities jumped to 7,152 from 6,706 deaths in the earlier year (Malaysian Road Transport Department, 2017). In addition, Malaysia had the highest fatality risk (per 100,000 population) among the Asian countries. The majority of road accident fatalities involve motorcyclists, making up 50% of the total number of accidents (Manan and Várhelyi, 2012). Unless action is taken, the number of deaths is expected to increase in the coming years.

Given all above, recent developments in laser scanning technology have improved spatial data acquisition in road environments. These developments have helped to build geometric road models that can help assessing road safety and make accurate and valid predictions on road traffic accidents. Laser scanning systems or LiDAR (Light Detection And Ranging) are the latest technology to capture the 3D geometry of various objects such as 3D point clouds on large surfaces accurately and densely.

Furthermore, they offer rapid and cost-effective data acquisition about road corridors and surrounding environments. Most of the road inventory information can be extracted from the original design of the roads. However, road geometric elements such as pavement roughness, vertical gradients, and horizontal curves change over time due to construction, degradation in road conditions, and vegetation growth (Shamayleh and Khattak, 2003). Apart from that, collecting data by conventional measurement methods are not safe, and the surveyor may not find safe sight distances to get readings necessary to calculate vertical grades and side slopes of the road (Uddin, 2008). The conventional measurement methods are relatively expensive to produce detailed topographic models and time-consuming. On the other hand, photogrammetry and optical satellite imagery have the disadvantages of poor visibility/ cloudy daytime, the relatively low accuracy of required topographic models, and computationally are not efficient to generate topographic maps due to the



requirements of collecting dense points distributed uniformly in the focus area (Uddin, 2008).

Therefore, LiDAR technology is a promising method for acquiring data about road corridors. In general, LiDAR sensors have higher spatial resolution than satellitebased sensors, wider Field of View (FOV), and lower cost than traditional aerial photogrammetric and surveying methods for right projects. By evaluating specific height information in LiDAR data, along with high-resolution orthophotos, objects such as road can be distinguished efficiently from other objects. Overall, LiDAR data is practical for extracting road geometry and roadside features that many applications including traffic accident modeling can benefit (Lee and Mannering, 2002). Thus, developing methods that can extract accurately and rapidly road information from LiDAR data to improve road safety is highly crucial.

One way to improve road safety is by developing accurate prediction models of traffic accidents using road geometry and sophisticated Machine Learning (ML) and statistical techniques. However, development of such models is not straightforward and needs careful analysis and optimization to be practical for transportation agencies.

The research of geometric road modeling from LiDAR data has progressed a lot since the development of advanced LiDAR systems. Various algorithms, data processing workflows, and practical guidelines have been proposed by different researchers and showed a significant performance compared to the traditional methods (Poullis and You, 2010; Fix et al., 2016). The latest methods combine LiDAR data with other ancillary information (e.g., road centerline, road attributes, knowledge about road shape and geometry) in hierarchical forms to create accurate three-dimensional (3D) models of road sections (Holgado- Barco et al., 2015). A hierarchical model (or a model with multiple levels of processing) is defined as a data processing model that combines sub-models (usually different algorithms) at several processing stages to solve specific problems. For instance, in a study by Holgado- Barco et al. (2015), a hierarchical model was developed by combining segmentation algorithms and Principal Component Analysis (PCA) to model road geometry from mobile LiDAR data. These methods have shown promising advantages over traditional methods. However, their main limitation is the dependency on the accuracy and the completeness of the ancillary information used to obtain the road features. Thus, progress should be made to overcome such limitations and advance the road extraction algorithms, and such developments will open up new areas for transportation applications.

The literature shows the momentous development of modeling approaches for predicting road traffic accidents including statistical and soft computing algorithms (Hosseinpour et al., 2014; Karlaftis and Vlahogianni, 2011; Pei et al., 2011). The traditional methods significantly focused on hand-crafted features identified by experts in the transportation field and used to model accident frequency and injury severity using statistical techniques such as Logistic Regression (LR) and Support

Vector Machine (SVM). However, as generating handcrafted features requires experts and time, researchers thought about alternatives such as Neural Networks (NN), Evolutionary Algorithms (EA) and developing powerful statistical models that can better handle accident data without expensive feature engineering (Yu et al., 2014). A part of these developments, the availability of data and having powerful computing resources such as processing on GPUs (Graphical Processing Units) have led to rethinking about NN methods. Deep Learning (DL), a recent groundbreaking development in ML community, has shed light on using NN models more efficiently than before. DL allows computational models to learn hierarchal representations of data with multiple levels of abstraction at different processing layers. In addition, in limited data situations, Transfer Learning (TL) can be used in DL models to overcome over-fitting problems. Overall, combining DL and TL with careful fine-tuning in a single workflow is expected to provide sufficient prediction power for models designed to simulate traffic accidents based on historical records.

Since the above shows the importance of having robust tools to model road geometry for road safety assessment, the primary goal of this thesis is to investigate issues surrounding the development of methods that can accurately and efficiently model road geometry and make predictions on road traffic accidents at high-speed expressways. This first chapter serves as an overview of the entire thesis.

Besides the state of the general topic and background of the study, it provides the statement of the problem, the gap of knowledge. The importance of the proposed research, the research questions, aims and research objectives, the thesis contribution, the scope of the topic, and outlines the order of information in the rest of this thesis.

1.2 The Statement of Problem

Everyone in this world wants to have safe transportation systems to travel from a place to another easily and securely. However, today there are many issues and challenges making transportation systems less safe than they should be. Among these issues, rapid urbanization over various landscape forms, population growth and migration of people from rural to urban areas. Other challenges include lack of technical tools that can support road safety managers to simulate future scenarios and make better plans to solve problems related to road safety efficiently. If these problems continue, failure of transportation systems would significantly affect the stability and development of modern cities as transportation systems are the heart of the cities.

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Specifically, there are a need to construct 3D models for highways and establish relationships among road geometry features (e.g., vertical and horizontal curves, side slopes) and road traffic accidents to improve safety assessments for road transportation. Research shows that using object-based methods (or OBIA—Object-Based Image Analysis) which take into consideration not only the spectral information, but also other geometric, textural, and contextual information for

extracting features from data is more powerful than pixel-based methods (Gudex-Cross et al., 2017). However, OBIA methods need careful optimization of the segmentation process and the choice of relevant features as well as rule sets that are transferable to other areas without significant loss of accuracy (Robb et al., 2015). Although many optimization methods have been proposed for OBIA, the proposed methods lack optimization of the two main steps of OBIA, segmentation, and classification at the same time. Choosing segmentation parameters that can produce the best the possible segmentation quality and classification accuracy will help producing more accurate and complete road features.

On the other hand, technical tools are essential to make predictions for future scenarios of road safety. There are two main groups of predictive models namely, statistical (e.g., LR) and computational intelligence (e.g., NN). The former requires extensive engineering works and significant efforts to extract relevant features for accident frequency and injury severity predictions. The latter requires relatively large datasets for training and careful optimization of model's hyper-parameters. NN due to limited data suffers from over-fitting, lack of generalization and computing the importance of accident predictors and modeling the temporal/contextual structures inherent in the accident data. The traditional feed-forward NN does not allow compositionality with the adequate flexibility to improve the generalization and predictive ability of the model. However, the recent DL methods allow compositionality and using accident data as sequential data allowing modeling their inherent temporal and contextual structures. With additional information such as spatial-temporal relationships among accident events, it is expected to improve the accuracy and generalization of the models. Additionally, the volume of traffic accident data usually plays a significant role in deciding a proper prediction modeling approach. With limited data (i.e., <500 records), simple models (i.e., statistical models with fixed parameters) are often preferred. However, some sophisticated modeling approaches such as DL models have higher prediction capabilities and attract many attentions in recent years. Their implementation with limited data requires the development of sophisticated models with TL methods, which the traffic accident literature lacks.

1.3 Research Objectives

The master goal of this thesis is to contribute to the efficient road geometric modeling from LiDAR data and to the prediction of traffic accidents on highways. For being practical, this objective has to be split up into smaller and more specific goals, which may be organized into methodological aims as follows:

- 1. To delineate road geometry in two dimensions (2D) using an integrated ACO and OBIA methods with a novel two-stage optimization strategy for the segmentation step.
- 2. To extract road geometry (i.e., 3D) from mobile LiDAR data using a hierarchal classification technique that combines Mean Shift (MS) segmentation, SVM, and PCA.



- 3. To develop and validate a Geometric Regression (GR) model for predicting the frequency of traffic accidents using road geometry information.
- 4. And, to develop and validate a Deep Learning approach using TL for forecasting the injury severity of road traffic accidents using historical accident records.

1.4 Research Questions

This thesis comprehensively addresses the following research questions:

1. OBIA based requires optimizing segmentation parameters (e.g., scale, shape, compactness). In this step, an objective function is designed to judge a sub-optimal combination of parameters that can achieve an accurate segmentation process as possible.

However, it is not known if optimization of segmentation and classification processes at the same time will improve the performance of feature extraction or not?

- 2. To what extent the integration of meta-heuristic optimization methods such as ACO and OBIA can improve modeling of road geometry.
- 3. Can hierarchical classification (combination of several algorithms) process mobile LiDAR data efficiently for delineating 3D road geometric features such as vertical gradients and superelevation?
- 4. GR is one of the modeling methods that can be used to model the frequency of traffic accidents. How efficient is this model for processing traffic accident data for the Malaysian context?
- 5. DL due to data availability and improvements in computing power is getting popular for many applications. How much is the prediction power of DL for modeling road traffic accidents? In addition, can new NN architectures such as RNN and Convolutional Neural Networks (CNN) outperform the traditional feed-forward NN?
- 6. Is TL an efficient method for modeling injury severity of traffic accidents of a limited volume data in the context of DL architectures or not?

1.5 Thesis Contributions

Significant efforts have been made in the literature on pursuing solutions for geometric modeling of roads from LiDAR data and advancing prediction models of road traffic accidents using both statistical and soft computing techniques. However, the existing studies still have some major concerns as discussed in Section 1.1 and Section 1.2. As a result, there is a need to develop new techniques or making improvements on the

existing techniques to provide better solutions for road safety assessment based on road geometry.

This thesis mainly contributes to the development of new methods for image segmentation, extracting road features in 2D and 3D from Airborne and Mobile LiDAR data, modeling accident frequency and injury severity using DL-based methods. First, it develops a new optimization strategy for OBIA classification based on a two-stage optimization approach. The method optimizes the two basic steps of OBIA, namely, segmentation and classification, to realize accurate road extraction from LiDAR data. This is achieved by selecting an optimal scale parameter first to maximize class separability and optimal shape and compactness parameters to optimize the final image segments.

The second contribution of this thesis is the development of a hybrid approach that combines ACO and OBIA-based feature extraction for LiDAR data classification and road geometry extraction. In this approach, ACO is used to find the best combination of features to use in OBIA for road extraction. In addition, since this approach only extracts 2D information of a road, it was necessary to develop a semi-automated approach for delineating 3D road geometry from mobile LiDAR data without information about vehicle trajectory, which the state-of-the-art methods lack.

Third, this thesis then goes beyond just extracting information about roads from LiDAR data but further uses that information with some additional data about road traffics and environment to make predictions on traffic accidents. In particular, it develops a model based on GR for predicting traffic accident frequency. Furthermore, it also designs and implements models based on DL such as RNN and CNN to simulate the injury severity of traffic accidents utilizing the temporal structure of accident data. Finally, when data on traffic accidents are scarce, this thesis provides a model that can work based on TL concept to overcome the need for DL models for large datasets and to avoid overfitting problems.

1.6 Scope of Study

This study has three main scopes as follows:

- 1. Only two types of LiDAR systems, airborne and mobile-based were studied for road geometry modeling, and other systems (e.g., terrestrial) were not investigated. The latter systems are efficient for detailed assessments of transportation assists (e.g., bridge, culvert, and tunnel) which is not the case of the current study.
- 2. The validations of these models in this thesis were based on an area in Malaysia. No transferability to other countries has been investigated due to the non-availability of data and permission to access to police reports on traffic accidents elsewhere. However, various experiments and evaluations were

conducted, analyzed and discussed on a comprehensive data that have more than a thousand of historical records of traffic accidents.

3. The data duration was from 2009 to 2015 due to the availability of the relevant data.

1.7 Thesis Organization

The thesis is split into five chapters.

The **first chapter** introduces the research topic and gives a brief background of the study, the statement of the problem, research questions and objectives, thesis contribution and significance of the study.

The **second chapter** provides an overview of the available models and discusses several important and relevant studies. It provides a cohesive review on several topics such as LiDAR, geometric road modeling, and traffic accident modeling.

The **third chapter** explains the various steps of data processing and analysis, which makes up the newly proposed models for geometric road modeling and analyzing road traffic accident data.

The **fourth chapter** discusses the results of the experiments and simulations conducted in the current research and presents evaluations of the proposed models on real datasets.

The **last chapter** summarizes the main findings of the research and offers recommendations for future work.

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