UNIVERSITI PUTRA MALAYSIA

DEVELOPMENT OF DEEP LEARNING-BASED FUSION METHOD FOR BUILDING DETECTION USING LIDAR AND VERY HIGH RESOLUTION IMAGES

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By

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Chairman : Associate Professor Helmi Zulhaidi Bin Mohd Shafri, PhD
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Buildings play an essential role in urban construction, planning, and climate studies. Extracting detailed and accurate information about building such as value, usage, height, and size provides information for town planning, urban management, and three-dimensional (3D) visualization. Building extraction with remote sensing data especially LiDAR (Light Detection And Ranging) and VHR (Very High Resolution) images is a difficult task and open research problem. For this purpose, scientists have been developing methods utilizing the standard pixel features and additional height features of the data in various ways. In urban areas, extracting buildings is more complex than extracting them in rural areas. This is because of the presence of nearby objects, such as trees, which frequently have similar elevations as buildings. Additional challenges also come from different material combinations that create a variety of intensity in the spectral bands, employed. Two common methods are widely used in literature, pixel-based and object-based methods (also known as OBIA). The former results in salt and pepper like noise in the detected buildings, while the latter requires proper feature selection and image segmentation. Both methods have poor generalization and transferability to other environments, scale dependency, and require good quality training examples. As a result, the main goal of this research is to design and optimize deep learning-based fusion techniques using Autoencoders (AE) and Convolutional Neural Networks (CNN) for integrating LiDAR and Worldview-3 (WV3) data for building extraction. The optimization was carried out using grid and random search techniques to improve the performance of models. Specifically, two fusion methods were developed. First, a method for fusion of LiDAR-based digital surface model (DSM) with orthophoto (LO-Fusion), and a second method for LiDAR-DSM with WV3 (LW-Fusion) image. The results of this thesis are promising. Our method achieved the highest accuracies of 97.34%, 94.48%, and 94.37% in the three-subset areas. It performed better than the

traditional methods, such as support vector machine (SVM), random forest (RF), and K-nearest neighbour (KNN). The highest validation accuracy in this group of methods was 89.04%, achieved by SVM. Although KNN achieved better training accuracy (92.34%) than RF, the latter achieved better validation accuracy than the former (86.17%). Furthermore, CNN and Optimized CNN with the random search were used to detect buildings in the same areas using only LiDAR and orthophoto data. The experimental results show that the use of additional features of WV3 image fused with LiDAR data can increase validation accuracy by almost 11%. The validation accuracy of Optimized CNN with only LiDAR and orthophoto data was 86.19%, which is relatively lower than those of SVM and RF. Overall, proper optimization can improve the use of deep learning models such as CNN and autoencoders to the extent of outperforming OBIA for building detection from LiDAR and VHR satellite data.

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

PEMBANGUNAN DALAM PEMBELAJARAN MENDALAM BERASASKAN GABUNGAN KAEDAH BAGI PENGESANAN BANGUNAN MENGGUNAKAN LiDAR DAN IMEJ RESOLUSI YANG SANGAT TINGGI

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Bangunan memainkan peranan yang penting dalam pembinaan bandar, perancangan, dan iklim. Mendapatkan maklumat yang tepat mengenai bangunan seperti nilai, penggunaan, ketinggian dan saiz memainkan peranan penting sebagai maklumat utama yang kritikal bagi perancangan bandar, pengurusan bandar, pengurusan bencana dan visualisasi tiga demensi (3D). Kebelakangan ini, kaedah berasaskan pelajaran mendalam, seperti rangkaian Neural mendalam (NN) dan model rangkaian Neural Convolutional (CNN), Autoencoders dan ensemble model telah mendapat banyak perhatian dalam aplikasi remote sensing, terutamanya untuk pengesanan objek (contohnya, pengesanan bangunan). Matlamat utama kajian ini adalah untuk merekabentuk pembelajaran mendalam berasaskan teknik gabungan bagi mengintegrasi LiDAR point cloud dan imej satelit Worldview-3 untuk pengesanan bangunan. Objektif khusus kajian adalah seperti berikut: (1) untuk merekabentuk dan membangunkan satu teknik penggabungan yang menggunakan Autoencoders mendalam dan rangkaian neural convolutional untuk pengesanan bangunan daripada data LiDAR dan Ortofoto, (2) untuk merekabentuk dan membangunkan kaedah gabungan yang mendalam bagi mengintegrasikan data LiDAR dan Worldview-3 untuk pengesanan bangunan, dan (3) untuk mengoptimumkan kaedah gabungan yang mendalam melalui grid dan teknik pengoptimuman carian rawak untuk meningkatkan prestasi model gabungan. Kajian ini telah membangunkan dua kaedah pengesanan bangunan berdasarkan teknik-teknik pembelajaran mendalam (cth., autoencoders, CNN) dan penggabungan data. Kaedah pertama merupakan kaedah untuk LiDAR DSM dan Ortofoto, dan kaedah kedua adalah untuk LiDAR DSM dan imej WV3. Dua set data telah digunakan: data LiDAR untuk pesawat, termasuk orthophotos dan imej WV3. Di samping itu, tiga kawasan bandar telah digunakan bagi menguji kaedah yang dicadangkan. Secara keseluruhan, hasil kajian

menunjukkan prestasi memberangsangkan berbanding kaedah lain. Kaedah pengabungan berasaskan pelajaran mendalam (DF) mencapai ketepatan yang paling tinggi iaitu sebanyak 97.34%, 94.48% dan 94.37% dalam tiga kawasan subset. Kajian medapati kaedah pembelajaran mendalam adalah lebih baik daripada kaedah tradisional, support vector machine (SVM), random forest (RF) dan K-nearest neighbour (KNN). Ketepatan paling tinggi dalam antara kaedah tradisional adalah 89.04%, dengan menggunakan SVM. Walaupun KNN mencapai ketepatan latihan lebih baik (92.34%) daripada RF, RF mencapai pengesahan ketepatan yang lebih baik daripada KNN (86.17%). Selain itu, CNN yang biasa dan CNN optima dengan carian rawak telah digunakan untuk mengesan bangunan di dalam kawasan yang sama dengan hanya menggunakan data LiDAR dan Ortofoto. Keputusan eksperimen menunjukkan bahawa penggunaan ciri-ciri tambahan imej data WV3 boleh meningkatkan ketepatan pengesahan oleh hampir 11%. Pengesahan ketepatan model CNN yang telah dioptimumkan dengan hanya menggunakan data LiDAR dan Ortofoto adalah 86.19%, agak rendah berbanding SVM dan RF. Berdasarkan keputusan ini, kajian-kajian pada masa hadapan perlu memberi fokus kepada kaedah pengoptimuman lain, seperti kaedah pengoptimuman Bayesian, dan teknik-teknik berasaskan pembelajaran gabungan yang lain menggunakan model yang lebih maju, seperti variational dan convolutional autoencoders.

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

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This is to confirm that:

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LIST OF ABBREVIATIONS

AE	Autoencoder
ANN	Artificial Neural Network
BSP	Binary Space Partitioning
BT	Brovey Transform
CNN	Convolutional Neural Network
CS	Component Substitution
DCA	Discriminant Correlation Analysis
DEM	Digital Elevation Model
DF	Deep Fusion
DL	Deep Learning
DSM	Digital Surface Model
DT	Decision Tree
ENVI	Environment for Visualizing Images
ESP	Estimation Scale Parameter
GA	Genetic Algorithm
GIS	Geographic Information System
GLCM	Gray Level Co-Occurrence Matrix
GPU	Graphical Processing Unit
GS	Gram Schmidt
ICA	Independent Component Analysis
IHS	Intensity Hue Saturation
IRS	Indian Remote Sensing

KNN	K Nearest Neighbor
LN	Linear
LO-Fusion	LiDAR-Orthophoto Fusion
LR	Logistic Regression
LSMA	Linear Spectral Mixture Analysis
LSTM	Long Short Term Memory
LW-Fusion	LiDAR-Worldview Fusion
MCC	Multi-scale Curvature
MLP	Multilayer Perceptron
MR	Multiresolution
MRA	Multiresolution Analysis
MRF	Multiresolution Segmentation
MS	Multispectral
NB	Naïve Bayes
NDTI	Normalized Difference Tree Index
NDVI	Normalized Difference Vegetation Index
NN	Neural Network
NOAA	National Oceanic and Atmospheric
OA	Overall Accuracy
OBIA	Object-Based Image Analysis
PAN	Panchromatic
PCA	Principal Component Analysis
PL	Polynomial
RBF	Radial Basis Function

RF	Random Forest
RGB	Red Green Blue
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
SAR	Synthetic Aperture Radar
SD	Standard deviation
SGD	Stochastic Gradient Descent
SIG	Sigmoid
SPOT	Satellite Probatoire d'Observation de la Terre
SRTM	Shuttle Radar Topographic Mission
SVM	Support Vector Machine
UAV	Unmanned Aerial Vehicle
UTM	Universal Transverse Mercator
VHR	Very High Resolution
WGS84	World Geodetic System 84
WV3	Worldview-3

CHAPTER 1

INTRODUCTION

This chapter first provides the background of study (Section 1.1). This section briefly explains the importance of buildings in modern cities and presents how spatial information is useful for applications require geo-data of buildings. Then, it states the research problem (Section 1.2) that this thesis solves and research objectives (Section 1.3), research questions (Section 1.4), and the main contributions of this thesis (Section 1.5). Finally, the significance of current research (Section 1.6), as well as thesis organization (Section 1.7), are presented.

1.1 Introduction

Buildings play an essential role in urban construction, planning, and climate. Extracting accurate information about the building such as value, usage, height, and size is critical for town planning, urban management, and Three-Dimensional (3D) visualization. With the advent of new remote sensing technologies such as LiDAR (Light Detection And Ranging), Very High Resolution (VHR) satellite imagery, building extraction is a major step in urban mapping, planning, and many other applications, such as land use, change detection analysis, disaster management, and site selection. However, building detection with these technologies at pixel or object level is a challenging task, especially in complex urban areas (Xu et al., 2018). This challenge is mainly because such areas are often characterized by complex structures, large intra-class, and low inter-class variations. These issues lead to inaccurate building detection with the existing methods. The task can be further complicated by an increase in spatial resolution and multisource datasets used. Several new techniques have been proposed to tackle some of these issues.

LiDAR data provide additional features that can increase the accuracy and quality of building objects. LiDAR offers an accurate and efficient approach to point cloud (elevation) data acquisition, which can be used to extract ground objects, such as buildings and trees. Unlike traditional photogrammetry methods, LiDAR systems can collect dense point clouds within a relatively short time. The additional advantages of these systems include high vertical accuracy and relatively low cost when used for the right projects. Many methods have been proposed to extract building objects from LiDAR or fused data from multispectral and LiDAR.

In recent years, the advancement of artificial intelligence applications with remote sensing techniques has emerged new approached to extracted refined information, specifically deep learning. Deep learning-based methods, such as Convolutional Neural Networks (CNN), Autoencoders (AE), and ensemble models have gained much attention in remote sensing applications, especially for object detection (e.g., building extraction). The main concept of deep learning models is extracting abstract representations from data, thereby reducing the complexity and necessity of feature extraction. Zhang et al. (2016) presented a technical tutorial of deep learning for remote sensing data. They discussed the practical aspects of designing deep learning-based models for remote sensing and suggested that low-level features (e.g., spectral, spatial, and textural), output feature representations, and the entire network architecture should be carefully addressed to achieve better results than traditional machine-learning methods. Consequently, developing accurate techniques for extracting building objects from remote sensing data using advanced methods such as deep learning can help advance various geospatial applications as mentioned above.

1.2 The Problem Statement

Buildings are fundamental elements in forming a city and essential for urban mapping. The extraction of accurate building objects from remote sensing data has become an interesting topic and has received increasing attention in recent years. Building extraction from remote sensing data is one of the long-standing and open research problems. Many methods have been developed for this purpose. Among the data sources, LiDAR and VHR aerial/satellite images have been found to be more efficient than other data sources due to the additional height features in LiDAR and fine spatial resolution of aerial and some satellite images.

In this context, the advantages of using LiDAR over traditional photogrammetry include the capability to collect dense point clouds at a relatively short time, high vertical accuracy, and low cost. However, the accurate extraction of buildings in urban areas with precise boundaries is a difficult task due to the presence of nearby objects, such as trees, which frequently have similar elevations as buildings (Sameen and Pradhan 2017). It was found that the fusion of LiDAR and aerial/satellite images has the potential to improve the quality of detecting overlapping objects. Therefore, it is suggested to use this approach for buildings detection.

Traditional methods of extracting buildings from remote sensing data include pixel-based supervised, unsupervised methods and OBIA have been found efficient for some cases (Alshehhi et al. 2017; Ji et al. 2018; Zhao et al. 2018). However, they often fail due to the complex and heterogeneous urban areas (Guo and Du 2017). Pixel-based methods result in salt and pepper effect like noise in the final maps; while OBIA based methods require careful handcrafting features and optimizing the segmentation process. Other problems of these classical methods include poor generalization, transferability to other environments, scale dependency, and the good quality training samples.

In contrast, previous studies (Yuan 2017; Bischke et al. 2017; Maltezos et al. 2017; Xu et al. 2018; Yang et al. 2018) have indicated the advantages of deep learning methods over traditional techniques for building detection. However, limited studies have investigated the power of deep learning for building detection from the fused of LiDAR and optical remote sensing images. Such concepts as AE and CNN in Deep Learning require optimization to exploit the advantages of both data sources for building identification. The optimization touches the hyperparameters of a designed model to reduce its sensitivity and the computing complexity. Therefore, careful designing for deep learning model and its optimization is required to extract fine buildings footprint.

1.3 Research Goal and Objectives

The main goal of this research is to develop an approach for deep learning based fusion techniques for integrating LiDAR point clouds and optical remote sensing data specifically Worldview-3 (WV3) and aerial orthophoto data, for building extraction. The specific objectives are as follows:

1. To design and develop fusion techniques using deep AEs and CNN for building extraction from LiDAR, orthophoto, and WV3 data.
2. To optimize the fusion methods via grid and random search techniques to improve the performance of the fusion models.
3. To assess and validate the developed fusion model and compare them to other benchmark methods.

1.4 Research Questions

This thesis attempts to find answers with experimental evidence for the following questions:

1. What are the advantages of fusing LiDAR data with very high-resolution satellite images instead of fusing LiDAR with orthophoto for building detection using deep learning methods?
2. What are the advantages and classification power of using deep learning methods over traditional machine learning techniques (e.g., support vector machine, random forest) for building detection?

3. Does AEs, as a dimensionality reduction technique, can improve the classification accuracy of building detection when used with the CNN model?
4. Which method between the grid and random search is superior to use for optimizing deep learning models for building detection from LiDAR and aerial/satellite image data?

1.5 Research Contributions

This thesis contributes to improving building detection from LiDAR, orthophoto, and VHR satellite image data. It contributes to the following research aspects:

- A design of a fusion technique based on deep learning models (i.e. CNN, AE) for building detection from LiDAR and orthophoto.
- The design of a deep fusion model integrates LiDAR and WV3 data for building detection with the new architecture.
- The evaluation of grid and random search optimization methods for fine-tuning deep learning models for building detection.

1.6 Significance of Research

Buildings are essential elements in cities, thus creating new building databases or updating old ones is an important task for city planners and managers. Building extraction from remote sensing data plays a major role in providing information for analysts and planners to generate useful data and enrich databases.

This research addresses several important points regarding building extraction such as data suitability and advanced fusion and detection methods as well as optimization techniques that can improve the overall performance of building detection workflows. It compares very high-resolution satellite images with aerial orthophoto for building detection, which provides information about how other researchers can advance the workflows in future upon the results from the current study. It develops and explains in details new deep learning based fusion methods for building detection from LiDAR and WV3 data. These new models can be a useful tool for updating existing databases in different organizations, thus making their data processing workflows more efficient.

1.7 Thesis Organization

This thesis is divided into five chapters as follow:

1. **Introduction** provides information about the background of the study, the statement of the problem, research goal and objectives, research questions, research contributions and significance of the research.
2. **Literature Review** explains the theory of methods used in this research and provides an overview, summary, and discussions on previous studies on building detection from remote sensing data.
3. **Methods and Materials** describe the overall methodology flowchart used in the current study, study area, datasets, a description of the proposed models with their processing details, and evaluation methods used to validate the results obtained from this research.
4. **Results and Discussion** describes the results obtained from this research; also, it provides detailed discussions on the experiments conducted on several datasets.
5. **Conclusion and Recommendations** summarize the major findings of this study and it offers recommendations for future works after explaining the limitations of the current work.

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LIST OF PUBLICATIONS

Al-Nahhas, F. H., Shafri, H. Z., Sameen, M. I., Pradhan, B., & Mansor, S.(2018). "Deep Learning Approach for Building Detection Using LiDAR–Orthophoto Fusion," Journal of Sensors, vol. 2018, Article ID 7212307, 12 pages, 2018. https://doi.org/10.1155/2018/7212307.

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