

Automatic updating and verification of road maps using high-resolution remote sensing images based on advanced machine learning methods

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the degree of

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under the supervision of Distinguished Professor Biswajeet Pradhan
and Dr Nagesh Shukla

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AUTHORSHIP/ORIGINALITY CERTIFICATE

I, Abolfazl Abdollahi, declare that this thesis, is submitted in fulfillment of the requirements for the award of Doctor of Philosophy in the faculty of Engineering and IT (FEIT) 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. This research supported by the Australian Government Research Training Program.

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“Your talent is God’s gift to you. What you do with it is your gift back to God.”

DEDICATION

This thesis is dedicated to my Wife and Parents.

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LIST OF ABBREVIATIONS

ADAM	Adaptive Moment Estimation
AEML UNets	Adaboost-Like End-To-End Multiple Lightweight UNets
AI	Artificial Intelligence
ANN	Artificial Neural Network
ASPP	Atrous Spatial Pyramid Pooling
BAL	Boundary-Aware Loss
BCL-UNet	Bi-directional ConvLSTM UNet
BConvLSTM	Bi-directional ConvLSTM
BL	Boundary Learning
BN	Batch Normalization
CasNet	Cascaded End-To-End
CDG	Coord Dense Global
CE	Cross Entropy
CEDL	Cross Entropy Dice Loss
cGAN	Conditional Generative Adversarial Network
CNNs	Convolutional Neural Networks
CP_clDice	Connectivity-Preserving Centerline Dice
CRFs	Conditional Random Fields
CycleGAN	Cycle Generative Adversarial Network
DA-CapsUNet	Dual-Attention Capsule UNet
DA-RoadNet	Densely Connected Blocks Called Dual-attention Network
DCCs	Densely Connected Convolutions
DCNNs	Deep Convolutional Neural Networks
DDSPP	Dense Dilated Spatial Pyramid Pooling
DEM	Digital Elevation Model
DenseNet	Densely Connected Convolutional Network
DH-GAN	Dual-Hot Generative Adversarial Networks
DL	Deep Learning
DLF	Dice Loss Function
DMM	Dirichlet Mixture Model
DNNs	Deconvolutional Neural Networks
DT	Decision Trees

ELU	Exponential Linear Unit
FCN	Fully Convolutional Network
FN	False Negative
FP	False Positive
FRN	Filter Response Normalization
FSM	Finite State Machine
FuNet	Fusion Network
GAN	Generative Adversarial Network
GAP	Global Average Pooling
GCA	Global Context-aware
GCB-Net	Global Context-Aware and Batch-Independent Network
GCPs	Ground Control Points
GIS	Geospatial Information Systems
HRSI	High-resolution Remote Sensing Images
HsgNet	High-Order Spatial Information Global Perception Network
ICN-DCRF	Inner Convolution Integrated Network and Directional CRFs
ILSVRC	ImageNet Large Scale Visual Recognition Challenge
IOU	Intersection Over Union
ITS	Intelligent Transportation Systems
KNN	K-nearest Neighbors
LiDAR	Laser Scanning of Light Detection and Ranging
LLF	Local Laplacian Filtering
LMs	Landscape Metrics
LP	Laplacian Pyramids
LSTM	Long Short-Term Memory
MCC	Matthews Correlation Coefficient
McGAN	Multi-Conditional Generative Adversarial Network
MCG-UNet	Multi-Level Context Gating UNet
MFB_FL	Focal Loss Weighted by Median Frequency Balancing
MIOU	Mean Intersection Over Union
ML	Machine Learning
MRENet	Multitask Road-Related Extraction Network
MRFs	Markov Random Fields

MsGAN	Multi-Supervised Generative Adversarial Network
MUNet	Modified UNet
OA	Overall Accuracy
OBIA	Object-Based Image Analysis
PCA	Principal Component Analysis
PReLU	Parametric Rectified Linear Unit
RBM	Restricted Boltzmann Machine
RCFs	Richer Convolutional Features
RDRCNN	Refined Deep Residual CNN
ReLU	Rectified Linear Unit
RF	Random Forest
RMSE	Root Mean Square Error
RoadVecNet	Road Vectorization Network
RRCLs	Recurrent Residual Convolutional Layers
RRCNN	Recurrent Residual CNN
RSRCNN	Road Structure-Refined CNN
SC-RoadDeepNet	Shape and Connectivity-Preserving Road Identification Deep Learning Network
SDF	Signed Distance Function
SE	Squeeze and Excitation
SEEDS	Super-Pixels Extracted via Energy-Driven Sampling
SGD	Stochastic Gradient Descent
SVM	Support Vector Machines
THEOS	Thailand Earth Observation System
TN	True Negative
TP	True Positive
TWS	Trainable Weka Segmentation
UAV	Unmanned Aerial Vehicle
UFCN	U-Shaped Fully Convolutional Network
UIter	Universal Iteration Reinforcement
WGAN-GP	Wasserstein Generative Adversarial Network with Gradient Penalty

AUTOMATIC UPDATING AND VERIFICATION OF ROAD MAPS USING HIGH-RESOLUTION REMOTE SENSING IMAGES BASED ON ADVANCED MACHINE LEARNING METHODS

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Abstract

One of the significant objects among urban features is the road network. Automatic road network extraction and vectorization from high-resolution remote sensing imagery (HRSI) is a major application in the field of remote sensing and geospatial information systems (GIS), which has a significant role in various purposes such as GIS maps updating, urban cover change detection, emergency tasks, navigation and so on. Nowadays, obtaining accurate information of road networks using various supervised and unsupervised segmentation and classification approaches from HRSI is a challenging task as they are changing very swiftly. In addition, various types of barriers like vehicles, trees, shadows, building roofs exist in the images with having the same spectral values and transparency as the class of road. Moreover, the structure of the road network is complicated and irregular. Traditional and manual methods for road network segmentation and vectorization that human operators manage are time-consuming and expensive. Recently, deep learning (DL) techniques have obtained efficient performance in the field of remote sensing images processing and features semantic segmentation. Therefore, in this research, the state-of-the-art deep convolutional neural networks (DCNNs) are applied for automatic and simultaneous road network surface segmentation and vectorization from different HRSI. The proposed models are capable of extracting road surface and vectorizing road networks simultaneously and efficiently as well as alleviating the shortcomings of the traditional machine learning (ML) and pre-existing deep learning methods for the given task.

Firstly, in objective 1, I solve the issues of conventional ML methods by implementing robust DCNN approaches for road surface segmentation from different HRSI. The presented networks are implemented to the various remote sensing datasets for road surface segmentation and compared with other state-of-the-art deep learning-based networks, which the results prove the superiority of the proposed networks in the road segmentation task.

Secondly, in objective 2, I propose a shape and connectivity-preserving road identification deep learning-based architecture called SC-RoadDeepNet to overcome the discontinuous results and road shape and connectivity quality of most of the existing road extraction techniques. The proposed model comprises a new measure based on the intersection of segmentation masks and their (morphological) skeleton called connectivity-preserving centerline Dice (CP_clDice) that aids the model in maintaining road connectivity. The qualitative and quantitative assessments demonstrate that the proposed SC-RoadDeepNet can improve road extraction by tackling shadow and occlusion-related interruptions and produce high-resolution results, particularly in the area of road network completeness.

Thirdly, in objective 3, I present a new automatic deep learning-based network named road vectorization network (RoadVecNet), which comprises interlinked UNet networks to simultaneously perform road segmentation and road vectorization with achieving important information such as width/length and location of the road network. Particularly, RoadVecNet contains two UNet networks. The first network can obtain more coherent road segmentation maps and the second network is linked to the first network to vectorize road networks. Classification results indicate that the RoadVecNet outperforms the state-of-the-art deep learning-based networks for road surface segmentation and road vectorization. In short, the proposed methods and the outcomes (high quality and accurate road network data) of the study has high potential in environmental applications such as land use change detection in urban areas, and emergency tasks and also commercial value in navigation and road maps updating.

Keywords: Deep convolutional neural networks; machine learning; remote sensing; road segmentation; road vectorization; road maps verification; road database updating