MACHINE LEARNING METHODS FOR ROAD EDGE DETECTION ON FUSED AIRBORNE HYPERSPECTRAL AND LIDAR DATA

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ABSTRACT

In the last decades, remote sensing sensors, such as hyperspectral systems or LiDAR scanners, have been used for urban mapping. However, an analysis in the urban environment is very complex in applications, e.g., road detection, city management, and urban planning. One of the important urban features is the detection of the road edges. In this study, an approach on multisensory hyperspectral and LiDAR data fusion (HL-Fusion) is introduced for road edge detection using different machine learning algorithms, such as Support Vector Machines, Random Forests, and Convolutional Neural Networks. The first results show that the Random Forest algorithm outperformed in the experiments on the study area at Oslo's surroundings in Norway. This study opens a window for further investigation on machine learning algorithms and a better understanding of HL-Fusion capabilities.

Index Terms— Hyperspectral, road edge detection, LiDAR, machine learning, data fusion, remote sensing

1. INTRODUCTION

Precise, cost- and time-efficient urban mapping has been an essential task for city management, navigation systems development, and more. One of the advanced methods in urban classification is airborne-based image analysis. In particular, road detection and road edge detection have proven to be crucial in each of those applications. Road edge detection has already been investigated in the computer vision research field using airborne-based RGB [1] and grey-scale images for rural areas [2]. For the automatic road detection approach from RGB-based images, diverse methods have been proposed [3, 4]. Although the RGB systems analysis is a conventional computer vision method, exceeding the visible range (0.4 – 0.7 μm) of the electromagnetic spectrum enables the use of multi- or hyperspectral imagery and dense spectral sampling for the latter [5].

In the last decades, active and passive remote sensing has been widely used for urban analysis, such as landcover mapping, urban planning, urbanization changes, biodiversity, and road detection [6]. Active remote sensing such as Light Detection and Ranging laser scanner (LiDAR) provides geometric and textural properties of targets and precise elevation extraction in a time-efficient way for large areas [7]. The elevation information can be used to differentiate between road and curbside. However, the automated classification of exact road edges based on LiDAR data is challenging due to its low spatial resolution and commonly one available wavelength, limiting the classification of complex urban structures based on their spectral signatures.

In comparison, the benefit of using passive remote sensing, such as hyperspectral imaging, is the ability to recognize the material properties due to its unique absorption features, called spectral fingerprints in the visible and near Infrared (VNIR: 0.4 – 1.0 μm) and the short wave Infrared (SWIR: 1.0 – 2.5 μm) [8,9].

The strategy to apply hyperspectral and LiDAR data fusion (HL-Fusion) has already been proposed by Weinmann et al. [10] for a small urban area. Their approach was to apply color and spectral information from VNIR hyperspectral and shape information from the LiDAR dataset for urban object classification, such as road, buildings, sidewalk, and vegetation. However, combining elevation information from LiDAR, such as normalized Digital Surface Model (nDSM), high spectral and spatial information from hyperspectral data (VNIR and SWIR), can help to deliver robust and accurate road edge mapping that includes spectral-spatial-elevation context [10, 11].

Machine learning algorithms are currently used to classify urban objects based on remotely sensed data. However, different algorithms achieve the best results when detecting different features. Therefore, knowledge is required on the features to be appropriately classified. Standard classifiers in urban landcover classification are Support Vector Machine (SVM) and Random Forest (RF). SVM handles high dimensional hyperspectral data and deals with small training datasets; therefore, it is widely applied in the urban analysis based on hyperspectral data [12], LiDAR [13], and HL-Fusion [14]. RF provides high accuracy of the hyperspectral data classification, high processing speed, retaining relevant spectral information without overfitting

Figure 1 Training dataset in Sandvika, Oslo surroundings in Norway (672x2560 pixels).

Figure 2 Test dataset in Sandvika, Oslo surroundings in Norway (480x1600 pixels).

[15]. Moreover, RF has also been used to LiDAR data [16] and different HL-Fusion methods reviewed by Debes et al. [17].

A more advanced classification method in deep machine learning is Convolutional Neural Network (CNN), applied for urban landcover mapping on hyperspectral data [17] and HL-Fusion [18], among others. CNN automatically learns abstract features and does not require prior knowledge about the class distribution in the hyperspectral scene [19].

In this study, we fuse hyperspectral and LiDAR data to extract road edges in Oslo and its surroundings. We apply machine learning algorithms, such as SVM, RF, and CNN, and compare them to each other in the road edge extraction.

The structure of this work is as follows. Section 2 presents the study area. In section 3, the methodology on the road edge detection based on HL-Fusion is explained. Section 4 provides the results and their discussion. Section 5 concludes the study and shows future perspectives and suggestions for further research.

2. STUDY AREA

The airborne hyperspectral and LiDAR data have been acquired simultaneously by the Terratec AS Company in August 2019 and April 2020. The dataset contained cloud-free airborne-based hyperspectral and LiDAR data over Bærum municipality near Oslo, Norway. The hyperspectral data were acquired using two HySpex sensors: VNIR-1800 (0.4 – 1.0 μm) and SWIR-384 (1.0 – 2.5 μm) with 0.3 and 0.7 m spatial resolution, respectively. The LiDAR data were acquired using ALS70 and Riegl VQ-1560i, with five emitted pulses per m^2 and intensity at 1.064 μm. The hyperspectral signatures were preserved using Nearest-neighbor interpolation. The study area shows a complex urban environment with various urban objects, such as road, vegetation, building, waterbody, train track (Figure 1, 2). In our experiments, we divided the study area into smaller parts due to the large files and high-dimensionality of the data.

3. METHODOLOGY

In this study, the following approach of HL-Fusion for road edge delineation was carried out. Two different HL-Fusions have been applied: 1) LiDAR and radiance data 2) LiDAR and reflectance data. Since the hyperspectral dataset contains data from two different sensors, VNIR and SWIR, the spatial resolution was unified to 0.3 m pixel size. The geocoded radiance data were converted to reflectance, adjusting illumination levels using ATCOR-4 (Atmospheric and Topographic Correction for airborne imagery) software [21]. For the radiance and reflectance data, individually, the Normalized Difference Vegetation Index (NDVI) was applied to mask the study area's vegetation. Further, the Principal Component Analysis (PCA) was applied to hyperspectral VNIR and SWIR data to reduce the high dimensionality of the data and extract spectrally homogeneous regions. The first three principal components (PCs) have been used as input for classification algorithms, covering 99.5 % variance.

The LiDAR-derived features include the intensity values of 1.064 μm from the first return and normalized Digital Surface Model (nDSM). For the HL-Fusion, hyperspectral and LiDAR data were geometrically coregistered [22]. The nDSM was used to mask out the elevated objects, such as trees and buildings. For the road edge delineation purpose, the study area's main urban objects except for roads have been masked in the image, such as train track, waterbody, vegetation (trees, grass), and buildings.

Since we implemented a supervised classification to identify roads, train tracks, vegetation, and waterbody, the labels have been generated manually pixel-wise directly from the training dataset retaining the pixel count similar for each class. For this study, the following machine learning algorithms, SVM, RF, and CNN, were applied to the radiance and the reflectance HL-Fusion data. We split the dataset in training – 70 % and testing – 30 %. For the CNN model, the training data are split into patches of 9x9 pixels each. Three convolution layers with 30 filters and 3x3 filter kernel sizes are applied to each patch. To minimize

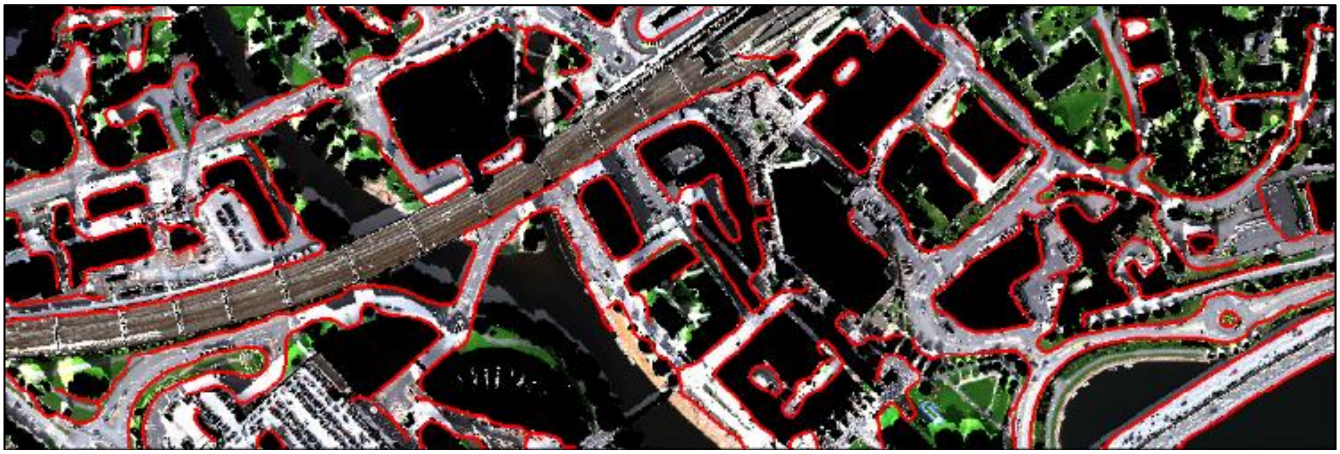

Figure 3 The first results for RF on road edge detection based on HL-Fusion.

Table 1 Comparison of classification results for reflectance (Ref) and radiance (Rad) HL-Fusions. F1 score corresponds to the road class.

	SVM		RF		CNN	
	Rad	Ref	Rad	Ref	Rad	Ref
OA [%]	83	92	**92**	**93**	80	77
F1 [%]	82	77	**88**	**79**	60	57
Time [s]	27.71	5.52	47.64	5.82	450.06	321.5

overfitting and enhance generalization, we add a dropout layer. We chose ReLU as the activation function, "categorical_crossentropy" as the loss function, and Stochastic Gradient Decent (SGD) as the optimization algorithm. Since the CNN training requires a large amount of data, we applied data augmentation by rotating, zooming, and flipping existing images. The final step was to delineate the road edges and produce a map with road lines applying the Canny Edge detector on the image, maintaining road and low vegetation classes.

4. RESULTS AND DISCUSSION

The classification results were evaluated, calculating the overall accuracy (OA), F1-score, and computation time (CT) (Table 1). The initial results show that the RF classifier outperformed for reflectance and radiance HL-Fusions compared to SVM and CNN algorithms, achieving 93 % accuracy (see Table 1). The RF can handle multiclass issues, is less sensitive to noise was already used for HL-Fusion [10]. CNN's poor performance can be related to limited training samples and high-dimensionality of the data, leading to overfitting and longer computing time. Figure 3 presents one of the first road edge delineation results for reflectance HL-Fusion-based RF classification, achieving 93 % accuracy.

However, there are misclassification spots in the road delineation results (Figure 3). One of the road detection challenges is the lack of identification of smaller roads, which can be caused by the too low resolution of the hyperspectral images and incorrect shadow classification. Another aspect is that the edges of some of the roads are not straight, broken, or misclassified. The main reason is that the road edges are often covered by buildings or trees in airborne-based images due to the inability of hyperspectral sensors to penetrate the surface.

Better F1 score road class results for each classifier for radiance data show that the atmospheric correction must not be required to achieve high urban object classification results. The reason is that any further processing steps can lead to artifacts misclassifying targets of interest. However, the multitemporal analysis results on radiance data may not deliver such a final overall accuracy of the classification since the reflectance data are more reliable and repeatable than radiance data.

5. CONCLUSION AND OUTLOOK

This study evaluated different machine learning classification algorithms for road edge detection based on HL-Fusion. Our main objectives were to provide insights into the capabilities of using multisensor data fusion in urban mapping, considering one of the essential features in many applications, such as road edge detection. The machine learning-based classifier – RF provided the best accuracy results for radiance and reflectance HL-Fusion.

Although deep learning analysis attracts more and more attention, ensemble learning has proved to be the best choice in this classification problem. However, we believe that deep learning is a promising basis for exploring HL-Fusion further and combining more algorithms in one analysis to improve data reduction, image segmentation, classification, and post-processing of the data.

The next step in this study will be to analyze multitemporal radiance and reflectance data from August 2019, April 2020, and September 2020. The proposed method will be tested in an area with known new roads not covered by the vector data, especially Oslo and its surroundings.

Further research will also explore how the HL-Fusion can be utilized to determine the microtopography along the roads and detect curbsides and other urban microstructures. We also want to explore deep learning algorithms' potential, collecting more training data and other deep learning algorithms to extract time-efficiently deep features in the spectral-spatial context and object-based classification.

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