Pixel-based and object-oriented classifications of airborne LiDAR and high resolution satellite data for building extraction

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Abstract. Building extraction from high spatial resolution data is a challenging task in the remote sensing community because of the spectral similarity between man-made objects, such as buildings, roads, and parking lots, in urban areas. This study utilizes two data types, Worldview-3 (WV3) and airborne Light Detection and Ranging (LiDAR), to extract buildings. The main goal of this study is to investigate the capability of these data sources and its effectiveness in fusing both to extract buildings. Different classification approaches, including pixel-based and object-oriented (OO) approaches, were applied to single WV3 and WV3 and LiDAR fused data. The support vector machine (SVM) was used for both classification approaches. Results show that the OO classification accuracies produced from the fused dataset was higher than that of the pixel-based dataset with 96% accuracy. Our findings also demonstrate that the fusion of LiDAR data with high spatial resolution satellite imagery can improve classification accuracy, especially for building extraction. The fusion of LiDAR data can also decrease the effect of spectral similarity between different man-made objectives in urban areas. The results also show that the OO approach has significant potential for building extraction by utilizing the WV3+LiDAR dataset.

1. Introduction

Building extraction from remote sensing data has been a challenging task within the remote sensing community. With the advent of very high spatial resolution data (VHR), such as WV3 and LiDAR, new opportunities have opened up for researchers and scientists. The WV3 has rich spectral, spatial, and textural information, whereas the LIDAR has rich vertical information. LIDAR data can provide highly accurate vertical information, which is useful for distinguishing urban objects (i.e., buildings) and is a more suitable cue than spectral and texture information [1]. Different classification techniques have been applied for building detection, such as unsupervised classification [2], object-based classification (Li et al. 2014[3]), and fuzzy logic.

The two aforementioned sensors can complement each other to obtain a robust description of the scenery. The fused spectral-spatial-elevation features of the two data sets will also be highly beneficial for further applications. The main goal of the current study is to investigate the effectiveness of fusing LiDAR data with WV3 for building extraction. Pixel-based classifiers ignore the spatial and textural characteristics of urban features, as well as produce mixed pixels and salt and pepper noise in the VHR image classification [4]. Data integration of VHR imagery and LiDAR products can overcome the vertical and horizontal heterogeneities of the urban environment [5].

Object-based image analysis (OBIA) has been applied in many VHR imagery mappings to overcome the associated problems with pixel-based classifiers, as well as address complexities that arise from the spatial and spectral heterogeneity of urban areas [6].

New sensors such as those on board of Worldview-3 satellite provide fine spectral and spatial signatures on urban features. Integrating Worldview-3 images and laser scanning point clouds can lead to accurate building extraction if proper fusion methods applied.

2. Methodology

2.1. Study area and datasets

The University Putra Malaysia (UPM) campus was selected as the study area for this research. This area is surrounded by different building types and vegetation (Figure 1). Two data sets were utilized: the WV3 and full waveform airborne LiDAR data. The WV3 image captured in 2014 was employed as the source of spectral, spatial, and texture information. These data contain eight spectral bands, four standard VNIR colors (blue, green, red, and near-IR1 with 1.24 m pixel resolution), and four added VNIR colors (coastal, yellow, red edge, and near-IR2 with 1.24 m pixel resolution). The full waveform LiDAR data captured over the same area in 2015 have a point density of 6 points per square meter. The study area is surrounded by many buildings of different sizes, shapes, and colors.
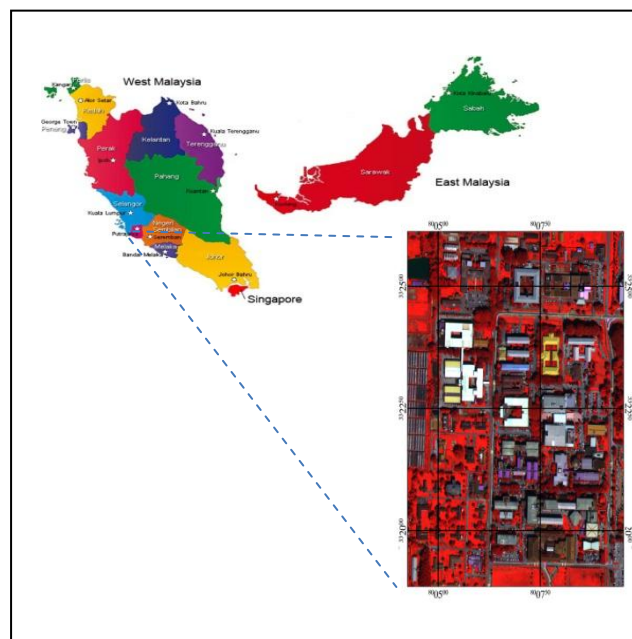

Figure 1: Study area at UPM.

2.2. Digital surface Model (DSM)

The digital surface model (DSM) data extracted from the LiDAR point cloud was utilized as the height information source. The point cloud was converted into raster layer with a pixel size of 0.25 m to utilize the information. Figure 2 shows the DSM raster layer of study area.

2.3. Fusion

A co-registration step, which is a necessary and crucial step in data fusion, was conducted before fusing the WV3 satellite image and 3D LiDAR points. The data-fused image was created by stacking the layers in ENVI software. The layers that include the eight spectral bands of WV3 and DSM data were stacked to fuse the two datasets.
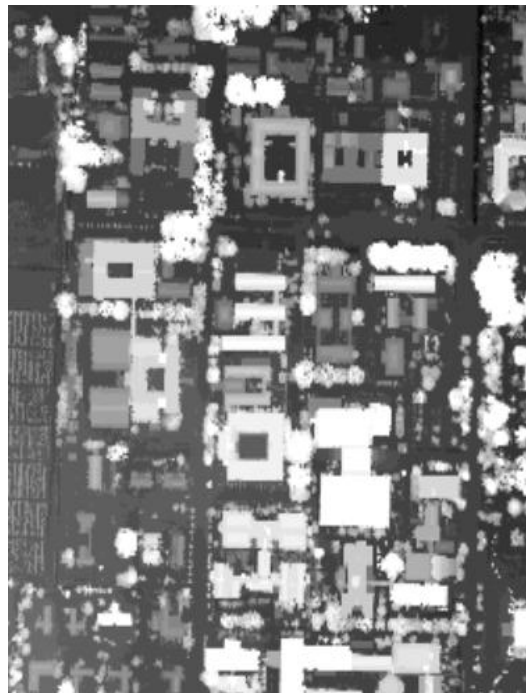
Figure 2. DSM extracted from the LiDAR data

2.4. Pixel-based classifications

Pixel-based classification analyzes the spectral properties of each pixel without considering the spatial and texture information related to the pixel of interest. Different studies have determined that several non-parametric and spectral-based classifiers, such as SVMs, have more significant potential for VHR urban classification compared with the Maximum Likelihood classifier [7]. SVM is popular in the remote-sensing community because of its ability to perform well when provided with only a few training sites [8]. A pixel-based classification of SVM was executed in ENVI software in the current study. The SVM was applied to the WV3 images and WV3+LiDAR datasets.

2.5. Object-oriented image analysis

The OO classification is a robust classifier that employs the image object rather than its pixels [9] and shows suitable results for feature extraction from VHR imagery [10]. The OB analysis attempts to group the spatially adjacent pixels into homogeneous objects and has been successfully applied to VHR image processing. The OO approach can decrease local elevation variation and generalize elevation information in a spatial neighbor [11]. OB was applied to the WV3 imagery and WV3+LIDAR by utilizing ENVI software.

2.6. Accuracy assessment

The classification result is invalid without an accuracy assessment. A confusion matrix was adopted to check the accuracy of the classification result. The testing data were employed as an input for the confusion matrix.

3. Results and Discussion

Our study focuses on building extraction from remote sensing data. A total of five classes were defined, namely, building, road, vegetation, water body, and shadows. The SVM classification approach that utilizes a radial bases function was applied on the WV3 and WV3+LiDAR datasets as shown in Figure 3.

The pixel-based result shows that all classes were classified with 59% accuracy, whereas the building classes were classified with 47% accuracy. The SVM classification result was improved when it was applied to the fused dataset with 86% overall accuracy (OA), whereas the building classes

had 82% accuracy. The OB approach was employed to fully utilize the information inherent in WV3 images, such as spectral, spatial, texture, and color information. The SVM classification algorithm was applied to all attributes derived from the fused dataset after creating the segments and extracting the features. The results show that the building was extracted with 96% accuracy and 97% OA as shown in Figure 4.
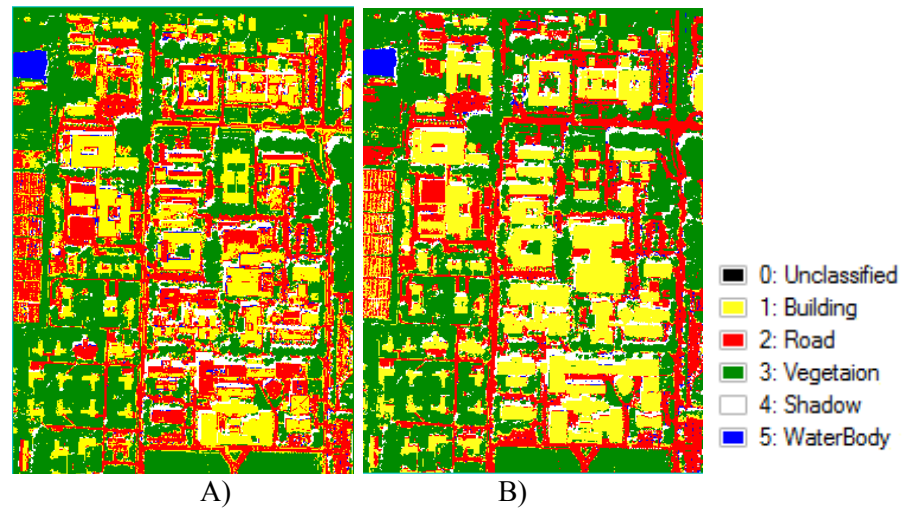
Figure 3. SVM classification on A) WV3 B) WV3+ LiDAR.
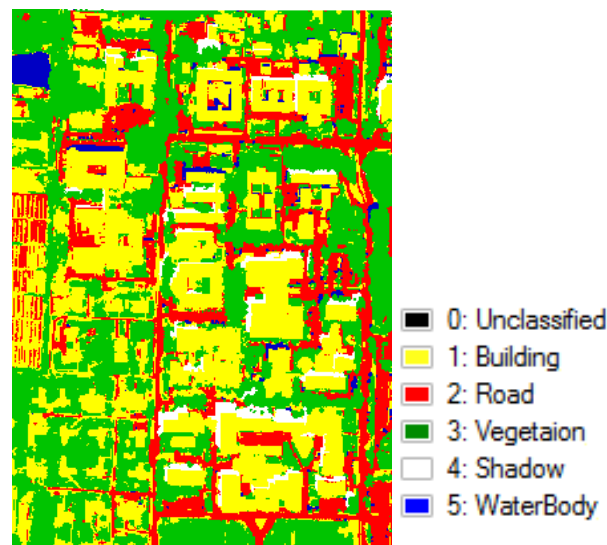
Figure 4. SVM classification applied on WV3+LiDAR data

Table 1 demonstrates the accuracy of different classification approaches applied on the WV3 and WV3+LiDAR datasets

Table 1. Accuracy of building extraction

Classification	SVM	SVM (Utilizing LiDAR)	OO
Overall Accuracy	59%	86%	**97%**
Building Class	47%	82.55	**96%**

4. Conclusion

The main goal of this study is to evaluate the effectiveness of fusing LiDAR data with high spatial resolution satellite images to extract buildings. Pixel-based classifications that utilize SVM applied to WV3 images yielded unsuccessful results because of the lack of sufficient spectral information and ignoring other information, such as spatial and texture information. Building class was extracted with only 47% accuracy. Many instances of misclassification occur between improvised surfaces, especially buildings and roads, because of the spectral similarity between these structures. An SVM classifier was applied to a fused dataset, and the results show that combining the LiDAR data with WV3 can improve classification accuracy of extracting a building by 35%. The highest OA (97%) was generated by the non-parametric SVM classifier that utilized layer stacking fusion data in the OO approach. The overall classification accuracies of the SVM that utilizes the pixel-based approach and OO that utilizes the WV3+LiDAR dataset improved by 35.5% and 49%, respectively. We also determined that the classification accuracies based on the layer stacking data were higher when the spatial, textural, and spectral information were employed. LiDAR and high spatial remote sensing fusion data provided better complementary information that LiDAR and VHR data alone. Therefore, the fusion of LiDAR and VHR data has significant potential for the highly accurate information extraction of objects and buildings.

Future work must focus on the full waveform LiDAR data and adoption of deep learning in fusing and classifying LiDAR data with satellite imagery to extract buildings. Nevertheless, a technique that can fully utilize information inherent in the full waveform LiDAR and extract different features from its data still needs to be developed.

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