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Image Fusion and Improving Classification Accuracy: A Survey

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Abstract

This paper focuses the image fusion of high-resolution satellite image and airborne light detection and ranging (LIDAR) data of urban area for improving classification accuracy. In urban area an image can be covered by numerous large buildings, skyscrapers, commercial and industrial structures, community parks, residential buildings, highways and bridges. Misclassification of shadows, water and roof gardens are major problem with such images. The various image fusion and classification technique in this paper were survived.

Keywords: Image fusion, Building extraction, classification, segmentation, urban environment

Introduction

Satellite images with high spatial resolution, such as those acquired using IKONOS-2, QuickBird-2, Geoeye-1, and WorldView-2, enable the superior detection of separate objects in complex urban areas compared with low or medium spatial resolution remote sensing data. However, the utilization of this type of data is challenging, in terms of the extraction and classification of image data. In particular, the building class typically found in land cover classes produces several problems for high spatial resolution images. First, the internal spectral variability of the building class increases, whereas the spectral variability between different classes decreases. Second, the building class exhibits a similar spectral reflectance to roads. Third, this class exhibits a diversity of spectral characteristics, such as gray, green, and red roofs. Fourth, the building class represents a generalization for a large set of man-made structures that vary in 3-D size (width, length, and height) and structural details (shape, roof structure, and building materials). Combined with variable lightening conditions and satellite sensor orientation, these issues can present difficulties in the classification of high spatial resolution images. The building objects in an urban area assume different shapes in 2-D and 3-D space. They also contain different colored roofs, including red, green, white, and gray. Therefore, it is difficult to classify buildings using only satellite images with high spatial resolution. However, additional information, such as texture and spatial characteristics, can be used for classification. Recently, a significant amount of research has focused on fusing optical images and airborne LIDAR data as an alternative solution. Fusing different types of data can prove effective when one data type presents an advantage during a specific process because the extraction of building objects in airborne LIDAR data provides a higher level of accuracy than the extraction of building objects in optical images. The basic idea behind in this paper is focus for fusion of high-resolution satellite image and airborne LIDAR data of urban area and obtaining the detailed information of an image by removing shadows and water region.

In this survey, a various image fusion and classification a technique performs preserves the image details effectively than other older technique. It provides a three-step process to minimize the misclassification of buildings and road objects. First, elevated road areas are detected in ground points, which are extracted for the generation of a digital terrain model based on statistical values. Second, building information is extracted from a satellite image through the output-level fusion of various data results. Third, supervised classification is conducted using a support vector machine for areas that lack elevated roads and buildings.

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Related works

X. Huang, L. Zhang and P. Li [1] proposed three step process. First, pixel shaped index (PSI) and structural feature set (SFS) is proposed to extract the statistical features of the direction-lines histogram. Second, some methods of dimension reduction, including independent component analysis, decision boundary feature extraction, and the similarity-index feature selection, are implemented for the pro- posed SFS to reduce information redundancy. Third, four classifiers, the maximum-likelihood classifier, back propagation neural network, probability neural network based on expectation– maximization training, and support vector machine.

L. Bruzzone and L. Carlin [2] categorizes these techniques into two blocks 1) a novel feature-extraction block that adaptively models the spatial context of each pixel according to a complete hierarchical multilevel representation of the scene and 2) a classifier, based on support vector machines (SVMs), capable of analyzing hyper dimensional feature spaces. The choice of adopting SVM-based classification architecture is motivated by the potentially large number of parameters derived from the contextual feature- extraction stage.

Q. Yu, P. Gong, N. Clinton, G. Biging, M. Kelly and D. Schirokauer [3] built a hierarchical classification scheme and selected features for each of the broadest categories to carry out the detailed classification, which significantly improved the accuracy. Pixel-based maximum likelihood classification (MLC) with comparable features was used as a benchmark in evaluating our approach. The object based classification approach overcame the problem of salt- and-pepper effects found in classification results from traditional pixel-based approaches. The classification and regression tree algorithm (CART) is used to classify the vegetation.

Y. Han, H. Kim, J. Choi and Y. Kim [4] proposed shape–size index (SSI) feature combines homogeneous areas using spectral similarity between one central pixel and its neighboring pixels. A spatial index considers the shape and size of the homogeneous area, and suitable spatial features are parametrically selected. The generated SSI feature is integrated with the original high resolution multispectral bands to improve the overall classification accuracy. A support vector machine (SVM) is employed as a classifier.

J. Holmgren, A. Persson and U. Soderman [5] proposed three step process in tree species identification: (1) delineation of individual tree crowns using LIDAR data; (2) estimation of tree height and crown area using LIDAR data; and finally (3) identification of species of the delineated tree crowns by combining features extracted from LIDAR data with features from multi-spectral digital image data. Values from the multi-spectral images were extracted for each LIDAR crown segment and were then used for the classification. By using the camera position (X0, Y0, Z0) and orientation of each image, the LIDAR generated tree crown segments were mapped to the corresponding pixels in the multi-spectral image. The extracted trees from the LIDAR data and the field measured trees were linked by using the tree positions estimated from LIDAR and as measured in the field.

D. S. Lee and J. Shan [6] considered the LIDAR data and IKONOS images as independent multiple bands to conduct the classification. To do so, the LIDAR elevation data is first resampled to the same ground spacing interval and stretched to the same radiometric range as the IKONOS images. An un-supervised classification (clustering) based on the ISODATA algorithm is then used to determine a class schema of six classes: road, water, marsh, roof, tree, and sand. The supervised classifications are then performed respectively for the original IKONOS four-band images and the five-band combined images using the maximum likelihood classifier.

M. Dalponte, L. Bruzzone, and D. Gianelle [7] proposed a new classification method by an analysis on the joint effect of hyper spectral and light detection and ranging (LIDAR) data for the classification of complex forest areas. They created three approaches 1) an advanced system for the joint use of hyper spectral and LIDAR data in complex classification problems; 2) an investigation on the effectiveness of the very promising support vector machines (SVMs) and Gaussian maximum likelihood with leave-one-out-covariance algorithm classifiers for the analysis of complex forest scenarios characterized from a high number of species in a multisource framework; and

3) an analysis on the effectiveness of different LIDAR returns and channels (elevation and intensity) for increasing the classification accuracy obtained with hyper spectral images, particularly in relation to the discrimination of very similar classes.

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In [8], T. L. Erdody and L. M. Moskai (2010) for this research discrete-return airborne LIDAR and high resolution color near-infrared imagery was used to estimate canopy fuel metrics in a ponderosa pine and traditional mixed conifer forest of eastern Washington state. A double sampling approach using regression models was utilized for ease of use and broad-scale applicability using easily available analytical tools. LIDAR and imagery data were used to create regression models in 3 different combinations: LIDAR only, imagery only and LIDAR and imagery fusion.

In [9], F. Rottensteiner, J.Trinder, S.Clode, and K. Kubik (2005) proposed a hierarchical technique for DTM generation and on the application of Dempster-Shafer theory for classification. These methods are used for building detection from LIDAR data and multi-spectral images.

In [10], G. W. Geerling, M. Labrador-Garcia, J. G. P. W. Clevers, A. M. J. Ragas,and A. J. M. Smits (2007) proposed a pixel based method which fuse the CASI and LiDAR-derived datasets on a pixel level and authors compared the classification results of the fused dataset with those of the non-fused datasets. The aim is to combine IS and LIDAR data by data fusion at the pixel level to improve the classification accuracy of an eight-class and five-class set of natural vegetation types. The eight-class set represents the vegetation classes relevant for nature and river management, while the five-class set serves as a minimum set to estimate hydraulic resistance for river-management purposes. The classification results of the fused data are compared with classification results of IS only and LIDAR only of the same dataset. The maximum-likelihood classification (MLC) was chosen to classify the data.

In [12], Y.Hu (2003) proposed an algorithms focus on automated extraction of DTMs, 3-D roads and buildings utilizing single- or multi-return LIDAR range and intensity data. First, DTM generation: An efficient framework has been developed to generate DTMs automatically for single- or multi-return range and intensity data in large datasets. The success of the algorithm is achieved by the effective combination of multiple component techniques including the hierarchical approach, smooth condition, data fusion, and interpolation methods. Second, road extraction: the integration of both the radiometry property of intensity data and the height information of the digital non-terrain model is highly feasible in reducing the misclassification of the road class. The reconstruction of grid road networks in urban areas is model driven, and is based on the global grid constraint. The road segment based hypothesis and verification strategy leads to efficient, robust, and automatic reconstruction of 3-D grid road models. Finally, building extraction: the boundary detection can reliably locate buildings from the height data and the vegetation support model. The building reconstruction can create prismatic models for flat roof buildings and polyhedral models for non-flat roof buildings.

In [13], Y. M. Kim, Y. D. Eo, A. J. Chang, and Y. I. Kim (2013) proposed a new mean planar filter (MPF) for segmentation that uses a 3×3 kernel to divide LIDAR data into planar and nonplanar surfaces. For extraction of ground points, a new method to extract additional ground points in forest areas is used, thus improving the accuracy of the DTM. The refinement process further increases the accuracy of the DTM by repeated comparison of a temporary DTM and the digital surface model. After the DTM is generated, building objects are extracted via a proposed three-step process: detection of high objects, removal of forest areas, and removal of small areas. High objects are extracted using the height threshold from the normalized digital surface model. To remove forest areas from among the high objects, an aerial image and normalized digital surface model from the LiDAR data are used in a supervised classification. Finally, an area-based filter eliminates small areas, such as noise, thus extracting building objects.

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In [14], J. C. Jimenez-Munoz, J. A. Sobrino, A. Gillespie, D. Sabol, and W.T. Gustafson (2006) shows a comparison between the land surface emissivity estimated with the Temperature and Emissivity Separation (TES) algorithm and from a simple approach using Normalized Difference Vegetation Index (NDVI) for ASTER images. In this paper two different methods have been applied to high spatial resolution and multispectral thermal data in order to retrieve land surface emissivity over an agricultural area: the NDVI method, which uses visible and near infrared data, and the TES data, which thermal infrared data. NDVI and Maximum-Minimum Difference (MMD) threshold have been proposed to classify the pixels into bare soil, green grass and senescent vegetation.

In [15], T. Schenk and B. Csatho (2002) describe two aspects of merging (fusion) aerial imagery and LIDAR data. The establishment of a common reference frame is an absolute prerequisite. Author solved this alignment problem by utilizing sensor-invariant features. Such features correspond to the same object space phenomena, for example to break lines and surface patches. Matched sensor invariant features lend themselves to establishing a common reference frame. Feature-level fusion is performed with sensor specific features that are related to surface characteristics.

Results and discussion

The various image fusion and classification algorithms for improving an image quality in this survey were studied. So, in this survey, the output-level fusion method effectively classified high-resolution satellite images of an urban area by enhancing the separability between the buildings, elevated roads, and road classes. The distribution-free support vector machine (SVM) classifier provided much higher accuracies than the other classifiers investigated. In particular, the elevation channel of the first LIDAR return was very effective for the separation of species with similar spectral signatures but different mean heights, and the SVM classifier proved to be very robust and accurate in the exploitation of the considered multisource data.

Conclusion

In this work it has been concluded that the image fusion and classification technique is more valuable in tradition in digital image processing applications and we presented a survey of image fusion and improving classification accuracy of misclassified images from the output level fusion of high-resolution satellite image and airborne LIDAR data of urban area. Even though there are several drawbacks with such image especially misclassification of shadow and water. So, a new technique for removing shadow and water region to improve image accuracy is proposed in my future work.

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