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Multiple-entity based classification of airborne laser scanning data in urban areas

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ABSTRACT

There are two main challenges when it comes to classifying airborne laser scanning (ALS) data. The first challenge is to find suitable attributes to distinguish classes of interest. The second is to define proper entities to calculate the attributes. In most cases, efforts are made to find suitable attributes and less attention is paid to defining an entity. It is our hypothesis that, with the same defined attributes and classifier, accuracy will improve if multiple entities are used for classification. To verify this hypothesis, we propose a multiple-entity based classification method to classify seven classes: ground, water, vegetation, roof, wall, roof element, and undefined object. We also compared the performance of the multiple-entity based method to the single-entity based method.

Features have been extracted, in most previous work, from a single entity in ALS data; either from a point or from grouped points. In our method, we extract features from three different entities: points, planar segments, and segments derived by mean shift. Features extracted from these entities are inputted into a four-step classification strategy. After ALS data are filtered into ground and non-ground points. Features generalised from planar segments are used to classify points into the following: water, ground, roof, vegetation, and undefined objects. This is followed by point-wise identification of the walls and roof elements using the contextual information of a building. During the contextual reasoning, the portion of the vegetation extending above the roofs is classified as a roof element. This portion of points is eventually re-segmented by the mean shift method and then reclassified.

Five supervised classifiers are applied to classify the features extracted from planar segments and mean shift segments. The experiments demonstrate that a multiple-entity strategy achieves slightly higher overall accuracy and achieves much higher accuracy for vegetation, in comparison to the single-entity strategy (using only point features and planar segment features). Although the multiple-entity method obtains nearly the same overall accuracy as the planar-segment method, the accuracy of vegetation improves by 3.3% with the rule-based classifier. The multiple-entity method obtains much higher overall accuracy and higher accuracy in vegetation in comparison to using only the point-wise classification method for all five classifiers.

Meanwhile, we compared the performances of five classifiers. The rule-based method provides the highest overall accuracy at 97.0%. The rule-based method provides over 99.0% accuracy for the ground and roof classes, and a minimum accuracy of 90.0% for the water, vegetation, wall and undefined object classes. Notably, the accuracy of the roof element class is only 70% with the rule-based method, or even lower with other classifiers. Most roof elements have been assigned to the roof class, as shown in the confusion matrix. These erroneous assignments are not fatal errors because both a roof and a roof element are part of a building. In addition, a new feature which indicates the average point space within the planar segment is generalised to distinguish vegetation from other classes. Its performance is compared to the percentage of points with multiple pulse count in planar segments. Using the feature computed with only average point space, the detection rate of vegetation in a rule-based classifier is 85.5%, which is 6% lower than that with pulse count information.

1. Introduction

In the past few years, ALS data have been widely used in urban applications, such as building extraction (Sithole and Vosselman,

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2004), building reconstruction (Oude Elberink and Vosselman, 2009a), building change detection (Murakami et al., 1999), bridge detection (Sithole and Vosselman, 2006), road extraction (Samadzadegan et al., 2009) and road reconstruction (Oude Elberink and Vosselman, 2009b). With the improvement of ALS data point density and accuracy, there are more and more high-level requirements for updating maps, disaster evaluation, illegal activity detection and high-level modelling, etcetera. Fine pre-processing of ALS data, such as high-level classification with high accuracy, is necessary for these requirements.

Most ALS data classifications are two-class problems, in which researchers focus on extracting one certain object. In other multiple-class cases, three classes are frequently used, namely: vegetation, building and ground (Samadzadegan et al., 2010), these are the elementary objects in urban areas. However, a multiple-class system with seven classes is rarely seen with lidar data. We, therefore, take on the challenge to classify the urban scene into the following classes: water, ground, building, vegetation and undefined object, in which "building" is further divided into roof, wall (including windows, balconies and all objects attached to walls), and roof element. There are two difficulties in this challenge: (1) Walls and roof elements are quite irregular in geometry, due to either various construction styles or a lack of data for walls and roof elements (mainly caused by occlusion or rainfall). It is hard to define proper attributes for them. (2) Roofs covered partly, or largely, by vegetation add another complication to the classification. When vegetation is both above roofs and near roof elements, the computer cannot distinguish vegetation from a roof element because they are both irregular in geometry and are above roof in space (shown in Fig. 1). In these areas, if entities are properly defined to calculate features, it will be easier to separate them.

There are many approaches to multiple-class classification problems using ALS data. Lafarge and Mallet (2011) use an energy function and Potts model (based on Li, 2001) to combine local features and local context. Chehata et al. (2009) select several best performance features from a large amount of possible features generated from both discrete-return and full-wave ALS data. Rottensteiner and Trinder (2007) fuse multi-spectral images and ALS data. Most of the approaches mentioned above use only one entity to extract features. The combination of multiple entities, however, has been seldom discussed in previous literatures. A portion of the existing classifications is implemented with point- (or pixel-) based features. These methods can obtain accurate classification results, but are time consuming for large data sets. Other works use segment or voxel-based features, which attempt to speed up the computation. Multiple-entity features are utilised in several literatures (Lim and Suter, 2009; Kim and Sohn, 2011). However, Lim and Suter (2009) did not study the impact of the entity on classification accuracy. Although Kim and Sohn (2011) generated point-based and object-based features, to achieve a classifier fusion, they used these two entities separately to generate two classifiers. Our assumption is that if points are organised in multiple ways to form multiple entities which are adaptive to different classes of interest, a few features will obtain high accuracy, and a multiple-entity strategy will achieve higher accuracy than a single-entity method.

To verify this assumption, we propose a strategy to classify ALS data which combines three types of entities. The impact of these entities on the overall accuracy, and the accuracy for each class of interest is also studied. Our research makes the following contributions:

1. Seven classes are classified simultaneously and directly on 3D lidar points. These classes are basic elements (ground, water surface, building, vegetation and undefined object) in an urban scene. To enhance the capability to perform building analysis and modelling, the building class is further divided into roof, wall and roof element.
2. A multiple-entity strategy is employed and researched. By analyzing the challenges in the urban scenes in Fig. 1, we generate three entities (planar/mean shift segments, and individual points) according to the characteristics of different classes. Meanwhile, the performances of multiple-entity classification and single-entity classification are compared.
3. The contextual information of a building is employed to separate walls and roof elements, and is proved to be a good feature for all types of walls and roof elements.
4. Five different supervised classifiers are tested, and the overall accuracy and the accuracy for each individual class is calculated and compared for each classifier.
5. We define a new feature, namely, "average point spacing" for classifying vegetation. The performance of "average point spacing" is compared to that of "multiple pulse count" information, and testing demonstrates it is a good feature for separating vegetation from other objects when the vegetation is not too dense. Conclusions on how well average point spacing performs in comparison with multiple pulse count are drawn from the research.

This paper is organised as follows: Section 2 contains a literature review on how various entities, features and classifiers are currently being used in ALS data classification methods. Our proposed entities, features for the entities, and our four-step classification strategy are all described in Section 3. The experiment data for this research are briefly introduced in Section 4, followed by Section 5 which contains the results for five different classifiers,

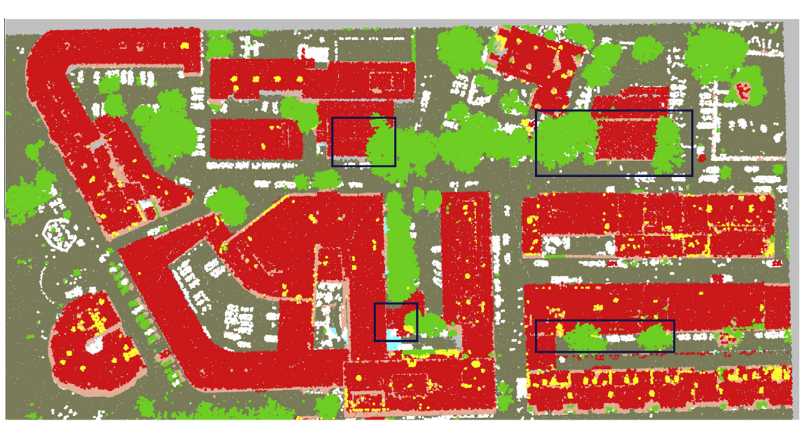

Fig. 1. Example of an urban scene. Many roofs are covered by vegetation in this area, roof elements and vegetation are not easily distinguished, as they both contain multiple pulse returns and have mutable shapes and sizes.