ISPRS Journal of Photogrammetry and Remote Sensing 128 (2017) 354–371

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

journal homepage: www.elsevier.com/locate/isprsjprs

Contextual segment-based classification of airborne laser scanner data

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ARTICLE INFO

Article history:
Received 14 December 2016
Received in revised form 17 March 2017
Accepted 21 March 2017

Keywords:
Point cloud
Segmentation
Classification
CRF

ABSTRACT

Classification of point clouds is needed as a first step in the extraction of various types of geo-information from point clouds. We present a new approach to contextual classification of segmented airborne laser scanning data. Potential advantages of segment-based classification are easily offset by segmentation errors. We combine different point cloud segmentation methods to minimise both under- and over-segmentation. We propose a contextual segment-based classification using a Conditional Random Field. Segment adjacencies are represented by edges in the graphical model and characterised by a range of features of points along the segment borders. A mix of small and large segments allows the interaction between nearby and distant points. Results of the segment-based classification are compared to results of a point-based CRF classification. Whereas only a small advantage of the segment-based classification is observed for the ISPRS Vaihingen dataset with 4–7 points/m^2, the percentage of correctly classified points in a 30 points/m^2 dataset of Rotterdam amounts to 91.0% for the segment-based classification vs. 82.8% for the point-based classification.

1. Introduction

Point clouds have become a standard type of data in production processes of digital terrain models, 3D city and landscape models, and land use maps. Whether produced by airborne laser scanning (ALS) or by dense matching of aerial photographs, classification of point clouds is required as the first step to extract the geo-information to be produced. While DTM production only requires a classification into ground and non-ground points, other processes typically require discrimination between multiple classes. Developed methods for point cloud classification can be categorised as point-based or segment-based, e.g. (Xu et al., 2012). Point-based classification makes use of point features, like pulse reflectance strength (lidar) or colour (image), as well as features characterising the point distribution in the local neighbourhood of the points, like surface smoothness or local normal vector direction. These features are calculated for every point and class labels are assigned point by point. In contrast, segment-based approaches first divide a point cloud into segments and assign class labels to segments such that all points within a segment obtain the same class label.

Potentially, segment-based classification has several advantages over point-based classification. First, segment feature values can be calculated by averaging over feature values of the points in a segment and may therefore better represent class characteristics. Secondly, segments contain more information than a point with its local neighbourhood. Therefore, a segment-based classification can use more features, like segment size, shape, percentage of last pulse echoes, or (variations in) point density. Such additional features may improve the class separability. Thirdly, segment-based classifications may be more effective in utilising context information. In point-based classification using probabilistic relaxation (Smeeckaert et al., 2013) or Conditional Random Fields (CRF; Niemeyer et al., 2014) the main use of context information is to ensure a local consistency of the point labels, e.g. based on models favouring a smooth labelling. In a segment-based classification, context is already intrinsically considered by the use of segments, which are expected to consist of points having similar properties and/or belonging to the same object. As segments can be very large, interactions between points that may be far apart from each other (*long range interactions*) are intrinsically modelled, which is even extended by an explicit model of context between segments belonging to different classes. Finally, as the number of segments is much smaller than the number of points, the classification can be much faster. This will, however, be partially offset by the time needed to segment the point cloud.

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http://dx.doi.org/10.1016/j.isprsjprs.2017.03.010
0924-2716/

The full potential of the above advantages can only be realised with a good segmentation. Under- and over-segmentation errors will negatively affect the classification accuracy. In particular, under-segmentation will inevitably lead to classification errors as a segment-based classification will assign the same class label to all points of a segment. To ensure under-segmentation is minimal, a strong over-segmentation is often preferred (Lim and Suter, 2009), similar to the use of super-pixels in image classification. However, features, like segment size or point density variation, become less useful in case of over-segmentation and in general all advantages diminish.

In this paper our goal is to improve point cloud classification by segmenting point clouds into as large as possible segments with rich descriptors and by making optimal use of these segments in a contextual classification. The scientific contributions are as follows:

– We propose the integration of multiple segmentation approaches for segment- and context-based classification. Combining different segmentation approaches is advantageous for a segmentation of point clouds containing objects of different point distributions. We expect this to provide a good starting point for contextual segment-based classification.
– For the contextual segment-based classification of point clouds based on a CRF, we propose the use of a local definition of the neighbourhood relations as the basis of the graph underlying the CRF, which is more flexible with respect to handling segmentations delivering segments of different shapes and spatial extents than a definition based on the arrangement of representative points of the segments as, for instance, in (Shapovalov et al., 2010).
– In this context, we also propose a new set of interaction features based on a local analysis of the point cloud in the vicinity of the segment boundaries, which will be used for a context model based on a generic classifier.
– We argue that very large segments corresponding to the ground and to standing water bodies can be identified reliably by simple heuristics. Nevertheless, we propose to consider these segments in the CRF-based classification as *fixed nodes* that will not change their class labels, but will contribute valuable context information.

This paper is structured as follows. We start with a discussion of related work in Section 2, focussing on methods for the segmentation and contextual classification of ALS point clouds. In Section 3, the new segmentation algorithm is described, and the methodology for CRF-based classification will be explained in Section 4. Section 5 presents a thorough evaluation of the approach using two data sets, comparing the results of the new method with a point-based classification and showing the advantages of considering context in the classification procedure. Finally, conclusions and an outlook on future work are given in Section 6.

2. Related work

This review on the related work focusses on the two main aspects of our new approach. We start with a discussion of related work in the field of ALS segmentation. After that, work on the classification of point clouds will be presented with a focus on contextual methods and on methods designed for ALS data.

2.1. Segmentation of ALS point clouds

Many algorithms have been developed for the extraction of surfaces from point clouds. Efficient RANSAC (Schnabel et al., 2007) and 3D Hough transform combined with surface growing (Vosselman, 2012) are often used in work to extract roof faces and other surfaces from airborne laser scanning data. While these methods often serve their purpose, they are not well suitable for segmenting the parts of a point cloud that cannot be described by surfaces. This review focusses on such non-parametric methods for point cloud segmentation. A more extensive survey of point cloud segmentation methods is provided by Nguyen and Le (2013).

Melzer (2007) presented a first study to apply mean shift (Comaniciu and Meer, 2002) to the segmentation of urban point clouds. Points on buildings, vegetation and terrain were already grouped by using mode seeking with only the X-. Y-and Z-coordinates. Finer segmentations were obtained when also making use of amplitude and pulse width of the echoes. Ferraz et al. (2010) used mean shift to separate surface vegetation, understory and overstory in forested areas. Yao et al. (2009) combined mean shift with normalised cuts to extract vehicles and flyovers. Rutzinger et al. (2008) used segment growing to cluster and classify vegetation points in an urban environment. Only the homogeneity in echo widths was used as a criterion for clustering neighbouring points. This feature typically distinguishes vegetation from smooth surfaces. Some over-segmentation in vegetation was observed because of variation in the echo widths within the vegetation.

More work on segmenting point clouds into non-planar segments has been performed with mobile laser scanning data. A typical workflow is to determine the points on the ground surface, remove those points from the dataset and then determine the connected components in the remaining point set (Douillard et al., 2010). Pu et al. (2011) and Velizhev et al. (2012) in addition incorporated scene knowledge to select components for further classification. Pu et al. (2011) eliminated large vertical components (walls) when extracting street furniture whereas Velizhev et al. (2012) selected on component size and distance to the ground when selecting cars and street lights. Golovinskiy and Funkhouser (2009) made initial estimates of background points (street level) and foreground points (street furniture, cars) and then used a min-cut based segmentation to improve the initial estimates.

Aijazi et al. (2013) segmented a point cloud generated by mobile laser scanning in two steps. After removing points on the ground the remaining connected components are segmented based on colour and reflectance strength. A two-step approach applied to airborne laser scanning point clouds has been presented by Xu et al. (2012). After an initial segmentation and classification of planar point sets, connected components of points with a doubtful classification were re-segmented using mean shift to generate new segments for a further classification. Vilariño et al. (2016) discuss a graph-based approach to segment point clouds in which each point instantiates a segment and segments are merged based on an analysis of within-segment and between-segment distances, similar to the graph-based image segmentation by Felzenszwalb and Huttenlocher (2004). Sima and Nüchter (2013) also include the differences in pulse reflection strengths in the calculation of distances between points when segmenting point clouds of indoor environments. As plane orientation is not included in the distance calculation, intersecting roof planes, but also adjacent roof and wall planes and adjacent wall and terrain surfaces may be merged to single segments.

2.2. Classification of ALS data

Techniques for the classification of ALS data can be characterised according to whether the classification is applied to the ALS points or to segments of ALS points, e.g. (Xu et al., 2012). Point-based classification has the advantage that a decision is taken for each point, so that the result will not be affected negatively by segmentation errors. On the other hand, as an individual