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A Survey on Shape Analysis tasks of ALS Roof Point Clouds

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Abstract
Air-borne laser scanned building point clouds have many applications in Geographic Information Systems (GIS), Remote Sensing, Archaeology, Photogrammetry and, Computer Vision. The advent of deep learning has led to significant improvements across various 3-D point cloud shape analysis tasks. Still, its effectiveness is not yet fully explored in remote sensing and GIS, especially for ALS building point clouds. Since the roof is the most informative part of the building from an airborne scan, 3-D modeling of buildings based on various roof styles is significant, and prior knowledge about roof style is advantageous for many applications. Automatic roof-top classification, retrieval, and shape completion using ALS building point clouds are relevant in this context, and performing these tasks with high accuracy is a great challenge. To enhance the future research in this field, this paper presents a comprehensive review of the recent progress in learning-based methods for ALS roof point clouds

Keywords: *ALS Roof, Point Cloud, Deep learning, Attention, Classification, Retrieval, Shape Completion.*

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I. INTRODUCTION

In recent years, there is an enormous demand for three dimensional (3-D) digital representations of building models across multiple domains such as Geographic Information Systems (GIS), Remote Sensing, Archaeology, Photogrammetry and, Computer Vision. These building representations can be used to recreate an entire

city model, which has multiple applications in urban modeling. Airborne laser scanning (ALS) point clouds are known to be an appropriate data source for urban modeling as it covers a large area quickly and directly provides spatial coordinates of various objects in the urban scene [1]. An ALS captures the overhead view of an urban scene consisting of various urban objects (e.g., trees, buildings, cars, trucks, poles, etc.), where buildings are the most prominent objects for urban modeling. The individual building point clouds are then segmented and extracted out for urban modeling tasks. These building point clouds mainly contain points of roof-tops, as the roof is the most informative part of a building [1,2].

The knowledge of the roof type and its geometry is very significant for various applications in urban modeling, indicating that shape analysis tasks such as classification, retrieval, and shape completion of ALS roof point clouds are relevant, well-studied research subjects. Previously, these techniques broadly fell into the categories of geometric or classical machine learning methods only and were limited by their capacity to work on complex roof shapes and noisy scans. Recently, deep learning has proven to be very successful across various ALS roof shapes for these tasks [3,4]. Section. 1.1 describes the existing works specific to ALS roof point clouds including the recent works using deep learning.

1.1 ALS Building Roof Modeling Techniques

One of the primary tasks in ALS roof modeling is reconstruction using which other sub-tasks like classification, segmentation, structuring, hypothesis generation can be inferred [5]. The existing strategies for ALS building roof reconstruction are classified into two main categories: model-driven and data-driven [6]. Model-driven or top-down (parametric) approaches require a predefined catalog (grammar-based) of basic roof shapes (e.g., flat, gable, and hip), and the most appropriate model is then selected from this available library to best fit the input point cloud [7,8,9]. The advantage of such model-driven methods is that the final roof shape is always topologically correct and relatively robust to noise, missing data, sparsity since we are directly reusing predefined roof models [10,11]. However, these methods require prior information about the roof style and can only reconstruct simple roof shapes (i.e., useful for tasks that do not require a high level of detail (LoD)) as these complex or arbitrary roof shapes are not included in the catalog [12]. One possible solution is to combine the simple building templates in the catalog and reconstruct complex roof shapes that are not defined in the template, thereby avoiding the need to expand the catalog with additional models [13].

In data-driven or bottom-up (non-parametric) approaches, simple geometric primitives such as points, lines etc are aggregated together to form the roof planes [14,15]. These data-driven methods are categorized based on the adopted techniques [11] such as segmentation [16,17,18], plane fitting [19], filtering and thresholding [20], and other learning-based methods [21,22]. A popular data-driven approach to reconstruct the roofs is to reassemble the planar patches derived by segmentation algorithms. The most common segmentation algorithms used for segmenting building roof planes are region growing [16,17] and RANSAC [18]. After segmentation, the geometric and topological relationships of the resulting segmented planes [16,17] are used to extract building shape cues such as intersection, step lines, outlines, and other surface primitives. Finally, roof models are reconstructed based on the extracted building modeling cues and refined using several regularisation and optimization operations [23,24].

Existing building reconstruction methods can reconstruct realistic 3-D roof models from ALS point clouds if the input point clouds are of high quality with sufficient density, noise-free, and complete [24,25]. If the input data is of low quality, the roof superstructures such as the chimney, dormers are usually considered noise and ignored during the reconstruction process, thereby reconstructing only coarse and basic roof models. Though several strategies have been proposed to solve this problem, most of them are not applicable in practice for a fully automatic large-scale reconstruction [13]. Therefore, there is a vital requirement for methods that can deal explicitly with the automatic reconstruction of small roof structures and have the ability to deal with low-quality roof point clouds. A class of data-driven methods called learning-based methods are specifically developed to generalize better to diverse and complex input data, but their application in ALS roof building modeling has not yet been fully explored.

1.1.1 Classification of ALS building roof point clouds

Existing research works for ALS roof style classification primarily rely on a set of predefined rules to identify certain roof styles. Hence, they suffer from low classification performance due to the use of heuristic rules and the assumptions regarding the geometry of these roofs [26]. While learning-based methods are meant to generalize better to a wide variety of roof types, there exist very limited works in ALS roof classification [26,27,28]. Zhang et al. [26] use a random forest classifier to train a bag of words feature extractor from the input point cloud. Then, a synthetic codebook is generated manually instead of learning from the sample data, and the proposed method achieves better classification performance in the given datasets. Castagno et al. [27] uses a multi-modal architecture utilizing both satellite images and Light Detection and Ranging (LiDAR) data as input. Pretrained CNNs extract features from the input satellite images and projected LiDAR images passed to support vector machines (SVM) or random forest classifiers to predict the roof shape. However, these classical machine learning algorithms like SVM, logistic regression, and decision trees suffer from computational complexities due to the high dimensionality of GIS data.

Deep Learning is another type of learning-based method which has shown great efficiency in various domains. Sarthak et al. [28] have attempted to perform roof classification using a point-based deep learning approach called PointNet. While their work directly extends an existing architecture for roof classification, such methods can perform the classification task with great efficiency and accuracy when compared to the classical methods. Shajahan et al. [3,4] has used novel deep learning techniques for classification and retrieval tasks on ALS roof point clouds which lead to better performance. These recent deep learning-based research works have contributed to the progress in this research area significantly. Also, these few works show that there is still better scope for utilizing more advanced techniques in Deep Learning for ALS roof shape analysis tasks.

1.1.2 Retrieval of ALS building roof point clouds

The retrieval of 3-D building roof models from model databases or the internet is a need of the hour for efficient urban scene reconstruction and real-world tasks [1,29]. This emphasizes the concept of data reuse and reduces the overall reconstruction cost, i.e., available roof models in a database having similar geometric shapes are reused rather than reconstructing ALS roof point clouds whenever they are acquired. Existing methods for roof model retrieval primarily use input queries as polygon models [31] while a few recent works have attempted to use point clouds [1,29]. The core idea in retrieval is to build a compact, efficient encoding of the building roof model, which can be compared to retrieve the closest matching shape. Chen et al. [1] have proposed a view-based method for 3-D building model retrieval using ALS point clouds. However, view-based methods yield reasonable retrieval results as they do not capture strong local features and are affected by self-occlusion [2]. Another work

[29], proposes to encode the input point cloud using low-frequency spherical harmonic functions (SHs) [29]. However, this decreases the ability to distinguish objects with similar geometric shapes, leading to ambiguity in shape description. Therefore, new strategies need to be investigated for developing more efficient methods for a consistent and accurate representation of building roof point clouds. This can be done by proposing deep learning methods which can encode better local geometric information and using the derived feature representation for fully automatic retrieval. Shajahan et al. [4] has introduced an innovative approach in deep learning using transformers for classification and retrieval tasks on an ALS roof dataset RoofN3D [32] which also gave better performance.

1.1.3 Shape Completion of ALS building roof point clouds

Shape completion is the process of predicting a complete roof shape given an input partial point cloud. ALS scans contain multiple imperfections, and the scanned point clouds can have missing regions due to incomplete scans, occlusions, etc. A hybrid approach for reconstruction of ALS roof point clouds involving deep learning and geometric methods has been developed to reconstruct lightweight building models with a level of detail 2 (LOD2) [31]. In this approach, the ALS building point clouds are first classified by deep reinforcement learning and then reconstructed by geometric methods. The reconstruction approach integrates the edge aware resampling algorithm and 2.5-D dual contouring for building reconstruction. Although this approach is capable of generalizing and reconstruct complex roof shapes precisely, semantic information is lost. Additionally, this method is not effective for large-scale datasets. To the best of our knowledge, there exists no published work with results for ALS roof shape completion using deep learning methods. Sarthak et al. [28] have made an attempt to try shape completion of ALS roof point clouds using a point-based deep learning approach called Point Completion Network (PCN). This work has shown that shape completion can be performed on ALS roof point clouds successfully, revealing that more advanced deep learning techniques can perform better.

II. CONCLUSION

From the above literature survey, we can infer that the existing traditional methods for roof classification, retrieval, reconstruction etc are dependent on manual intervention and has several limitations. Compared to these methods, deep learning-based methods give high performance and better suitability for ALS roof point clouds. As there is a recent progress in deep learning-based in this area, more advanced techniques are expected to be introduced soon for ALS roof point cloud related tasks.

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