ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume V-2-2022
XXIV ISPRS Congress (2022 edition), 6–11 June 2022, Nice, France

AUTOMATIC TRAINING DATA GENERATION IN DEEP LEARNING-AIDED SEMANTIC SEGMENTATION OF HERITAGE BUILDINGS

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Commission II, WG II/8

KEY WORDS: Training data, Automation, Deep learning, Point cloud, Heritage, Semantic segmentation.

ABSTRACT:

In the geomatics domain the use of deep learning, a subset of machine learning, is becoming more and more widespread. In this context, the 3D semantic segmentation of heritage point clouds presents an interesting and promising approach for modelling automation, in light of the heterogeneous nature of historical building styles and features. However, this heterogeneity also presents an obstacle in terms of generating the training data for use in deep learning, hitherto performed largely manually. The current generally low availability of labelled data also presents a motivation to aid the process of training data generation. In this paper, we propose the use of approaches based on geometric rules to automate to a certain degree this task. One object class will be discussed in this paper, namely the pillars class. Results show that the approach managed to extract pillars with satisfactory quality (98.5% of correctly detected pillars with the proposed algorithm). Tests were also performed to use the outputs in a deep learning segmentation setting, with a favourable outcome in terms of reducing the overall labelling time (-66.5%). Certain particularities were nevertheless observed, which also influence the result of the deep learning segmentation.

1. INTRODUCTION

As the documentation of heritage objects is undertaken more and more in 3D, point cloud data has become ubiquitous in the heritage community. With the advent of laser scanners and advanced photogrammetric processing, the documentation process is becoming more and more streamlined. The next issue of interest in the point cloud processing community is how to annotate the geometric point cloud with the addition of semantic attributes. This is required when the point cloud is needed for analysis, modelling, and predictions. A semantically annotated point cloud can thereafter be used to create information-rich 3D GIS and/or HBIM (Heritage Building Information Models) (Campanaro et al., 2016).

Machine learning (ML), and more precisely deep learning (DL) techniques, has witnessed a surge in overall interest in this age of big data (Bello et al., 2020). The possibility to use large quantities of data to train the computer to perform semantic segmentation automatically is indeed a very interesting concept and currently a promising field of research, as it provides a robust segmentation result with quick processing time. However, the main bottleneck problem in implementing DL techniques is mainly related to the availability of labelled datasets (Maalek et al., 2019). In the case of heritage point cloud, this problem is exacerbated by the diversity of classes and architectural features, as well as the general lack of labelled datasets. As such, the usual way to obtain training data is by manual annotation (Malinverni et al., 2019).

Considering these issues, a combination of more traditional segmentation based on geometric axioms and DL techniques will be presented in this paper. In particular, deep learning techniques will allow validating objects segmented by traditional methods. The algorithmic segmentation uses the functions in the Matlab toolbox M_HERACLES to generate training data for the DL technique. The toolbox is a set of Matlab functions (https://github.com/murtiad/M_HERACLES, accessed 4 October 2021) specifically developed to perform semantic segmentation on heritage objects (Murtiyoso and Grussenmeyer, 2020).

While the geometric approach may be used to directly generate segmented point cloud, many limitations are inherent in this method. Indeed, this type of approach mainly uses case-specific hard-coded prior knowledge and geometric rules in each function, therefore limiting its use for a holistic semantic segmentation. This rigidity is however counterbalanced by rapid processing time and a straightforward and open nature as opposed to the more closed system of DL techniques. As such, we postulate that both geometric rules-based and DL methods have their own advantages and disadvantages which may play well to support each other.

The main idea proposed in this paper is therefore to use the two semantic segmentation approaches, namely the geometric rules-based and DL methods, to complement each other. Our proposed method therefore tries to automate as much as possible the semantic segmentation workflow in the case of

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