OPALS and Sparse CNN for ALS Point-Cloud Classification

Nguyễn Vũ Hải
Thai Nguyen University of Information and Communication Technology
Thai Nguyen University, Thai Nguyen, Vietnam
student594@ictu.edu.vn

***Abstract*—This undergraduate thesis investigates OPALS preprocessing and sparse convolutional neural networks for classifying airborne laser-scanning data. Airborne laser-scanning point clouds need reliable labels for ground, vegetation, buildings, and other objects. The student preprocesses Vienna City ALS tiles with OPALS and trains a sparse CNN on smaller point-cloud patches. The report describes five training epochs and evaluates the selected model on two held-out test tiles. The source reports class average precision on Test Tile 1 of 0.9918 for ground, 0.9410 for vegetation, 0.9679 for buildings, and 0.6663 for other objects; Test Tile 2 reports 0.9832, 0.9705, 0.9717, and 0.7414 respectively. The weaker other-object class is linked to sparse and varied training examples. The reported results apply to the specified Vienna tiles and hardware. The thesis does not establish transfer performance on other cities, scanners, or class distributions. The contribution is a documented student study or prototype whose stated scope can guide further testing.**

***Index Terms*—ALS, OPALS, sparse CNN, point-cloud classification**

I. Introduction

Airborne laser-scanning point clouds need reliable labels for ground, vegetation, buildings, and other objects. This thesis investigates OPALS preprocessing and sparse convolutional neural networks for classifying airborne laser-scanning data. It begins from a practical engineering need and explains the technologies and workflow chosen for the case. The objective is to document a student implementation or comparative investigation, together with the evidence available in the manuscript. Broader operational or economic effects require separate measurements and are not assumed from the existence of a prototype [1]. Related published studies provide context for the subject and methods [2], [3], [4], [5], [6], [7], [8], [9], [10]. These contextual works were selected for this English summary; they are not asserted to appear in the original thesis bibliography.

II. Methods

The student preprocesses Vienna City ALS tiles with OPALS and trains a sparse CNN on smaller point-cloud patches. The report describes five training epochs and evaluates the selected model on two held-out test tiles. The source is summarized through its stated design, implementation material, examples, and conclusion. Features shown in the manuscript are distinguished from proposals for later development. This review does not add a new experiment, fill missing measurements with estimates, or treat a planned capability as an observed result. The source thesis remains the provenance for the reported work [1].

Supervisor: Trần Quang Quý, Thai Nguyen University of Information and Communication Technology (tqquy@ictu.edu.vn).

III. Results

The source reports class average precision on Test Tile 1 of 0.9918 for ground, 0.9410 for vegetation, 0.9679 for buildings, and 0.6663 for other objects; Test Tile 2 reports 0.9832, 0.9705, 0.9717, and 0.7414 respectively. The weaker other-object class is linked to sparse and varied training examples. The report's screens, configurations, examples, or measurements constitute the evidence for this summary. A capability described only as a design intention is not counted as a validated operational outcome. No additional performance, adoption, financial, or safety figure has been introduced here. The result is interpreted within the scope of the student's documented setup [1].

IV. Discussion

The reported results apply to the specified Vienna tiles and hardware. The thesis does not establish transfer performance on other cities, scanners, or class distributions. Further work could add examples of rare objects and test the same pipeline on independent ALS collections with explicit class-wise metrics. These limitations affect how the evidence should be read. The current manuscript can support understanding of the design and reported demonstration, while independent tests would be needed for stronger claims. Any later deployment should document its environment and separate observed outcomes from intended benefits [1].

V. Conclusion

The thesis documents OPALS preprocessing and sparse convolutional neural networks for classifying airborne laser-scanning data. The source reports class average precision on Test Tile 1 of 0.9918 for ground, 0.9410 for vegetation, 0.9679 for buildings, and 0.6663 for other objects; Test Tile 2 reports 0.9832, 0.9705, 0.9717, and 0.7414 respectively. The weaker other-object class is linked to sparse and varied training examples. The reported results apply to the specified Vienna tiles and hardware. The thesis does not establish transfer performance on other cities, scanners, or class distributions.

Further work could add examples of rare objects and test the same pipeline on independent ALS collections with explicit class-wise metrics. Accordingly, the present contribution is a source-grounded account of the student work and its tested or illustrated scope. Claims about broader effectiveness should be assessed in later work using explicit evaluation conditions [1].

References

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