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| **Virtual forests and unsupervised domain adaptation for training deep learning-based models for tree analysis from LiDAR point clouds** |
| Deep learning algorithms have recently achieved state-of-the-art performance in tasks such as individual tree classification, part segmentation and tree analysis using 3D LiDAR point cloud data of forests. One of the main downsides of deploying supervised deep learning is the need for extensive training datasets, i.e. LiDAR point clouds that have been annotated for target tasks (e.g. tree part labels) by human experts, that are used to train models that can process new, unseen data. One strategy for addressing this issue, which has shown success in applications outside of forests, is the use of simulated synthetic data (with automatically generated annotations) for training deep learning models which are deployed on real target data/environments.  In this talk, we explore and evaluate the use of biologically-accurate virtual forest stands (including simulated tree growth/structure and simulated LiDAR scanning processes) to be used to train deep learning models for analysing trees for LiDAR point clouds. We have developed a high-fidelity tree simulation pipeline which simulates a variety of different tree structures and scanning processes which can be used to generate large datasets of synthetic trees with automatically annotated per-tree attributes, without the need for human expert annotation. We develop deep learning models for tree part segmentation and estimation of tree parameters such as stem diameters, stem volume and branching structure which are then trained using our synthetic tree data. We have also developed a unsupervised domain adaptation method which uses un-labelled, real LiDAR data from the target environment to fine-tune the model, which is then deployed on real LiDAR datasets.  Results of our approach are shown across high and medium resolution LiDAR captures from both mobile terrestrial and airborne laser scanning of several plantation forest environments in Australia and New Zealand (resolutions ranging from 300-8000 points per m2). We compare performance metrics for tasks such as tree part segmentation when models are trained using synthetic data vs. real LiDAR datasets. Our results show that models trained on our synthetic data pipeline can outperform models trained on real LiDAR data, in particular when real data-trained models only have access to training data from non-target sites. We also demonstrate that the use of unsupervised domain adaptation methods further improves the accuracy of synthetically-trained models.  Outcomes of our study have implications for reducing the burden required in manual human expert annotation of large LiDAR datasets required to achieve high-performance from deep learning methods for forest analysis. The use of synthetically-trained models shown here provides a potential way to reduce the barriers to the use of deep learning in large-scale forest analysis, with implications to applications ranging from forest inventories to scaling-up in-situ forest phenotyping. |