Knowledge-based learning for plant phenotyping

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1 Introduction

Plant phenotyping, an effort to assess plant physiology traits such as growth, architecture or profile, and quantitative measurements, has been on a rising trend for its importance in understanding functioning and cultivation of plants for sustainable agriculture. The trend is mainly supported by emerging technologies in imaging and sensing (Li et al., 2014), and then, artificial intelligence (Ubbens & Stavness, 2017).

Correspondingly, we attempt to automate the recognition of plant architecture from remote sensing LiDAR (laser imaging, detection, and ranging) data based on our related works in species modeling (Gobeawan et al., 2021) and recognition (Chattoraj et al., 2022).

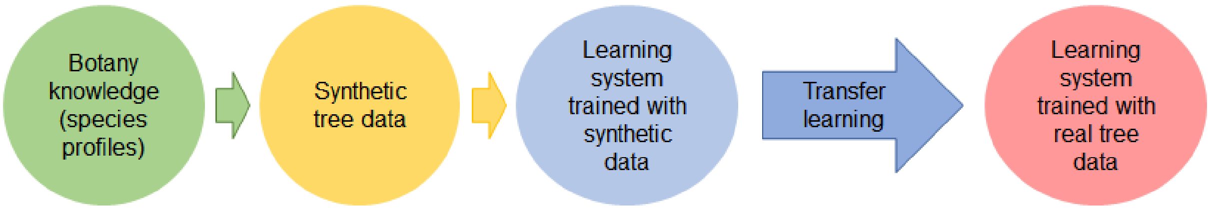

Figure 1: Knowledge-based learning of tree species profiles

2 Data and Methods

To recognise profiles or plant architecture aspects of LiDAR tree data, we develop a knowledge-based learning methodology (Figure 1) which learns the profiles of synthetic species model data, adjusts the learning from real tree data, and then uses this refined learning system to recognise the profiles of other real tree data (Chattoraj et al., 2022). The knowledge-based learning has an advantage of training on ideal data instead of noisy, limited LiDAR real tree data.

Our methodology leverages species modelling work (Gobeawan et al., 2021) to synthesise a large number of noise-free tree species data for training the machine. The synthesis data are generated based on the botany knowledge which allows a controlled learning to focus on each profile parameter.

3 Results and Discussion

We present preliminary results of the knowledge-based learning for recognising four species profile parameters in (Chattoraj et al., 2022): phyllotaxis type (alternate/opposite/n-whorled), phyllotaxis divergence angle (steps within 0-360 degrees), branching mode (monopodial/sympodial), and branching delay (0 to n years). For training the learning system, 1000 labeled, synthetic species models and 38 real tree models (leave-one-out for testing) are used, with effectively 38 real tree models for testing.

There is a total of 11 species in the whole datasets. Each dataset corresponds to a unique species profile configuration on a list of comprehensive profile parameters (Gobeawan et al., 2021). The current preliminary results correspond to just learning four parameters. The test results are summarised in Table 1 which shows potentially higher accuracy of our proposed knowledge-based learning method over a generic machine learning model to recognise species profile parameters.

Table 1: Knowledge-based learning accuracy for recognising four tree profile parameters on real trees

Experiment	Phyllotaxis type	Divergence angle	Branching mode	Branching delay
Machine learning	0.763	0.711	0.737	0.632
Knowledge-based machine learning	0.842	0.734	0.789	0.658

Profile parameters with clear categorical values such as the parameter *phyllotaxis type* are suitable for learning by classification. However, profiling parameters of different natures often involves some simplifications or assumptions of the parameter values. For example, the value ranges of parameters *divergence angle* and *branching delay* are continuous and non-discrete, while the values of parameters *branching mode* and *branching delay* may vary over time for different tree parts. However, those profile parameters are regarded as discrete variables in our knowledge-based learning.

As a work-in-progress, our knowledge-based learning system will progress to recognise a comprehensive range of profile parameters as listed in (Gobeawan et al., 2021).

4 Conclusion

We have developed a knowledge-based learning to recognise species profiles or tree architecture aspects of an individual tree. Such learning system may fully automate plant phenotyping which will be useful for horticulture and sustainable agriculture.

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