A Synthetic Wheat L-System to Accurately Detect and Visualise Wheat Head Anomalies

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Abstract. Greater knowledge of wheat crop phenology and growth and improvements in measurement are beneficial to wheat agronomy and productivity. This is constrained by a lack of public plant datasets. Collecting plant data is expensive and time consuming and methods to augment this with synthetic data could address this issue. This paper describes a cost-effective and accurate Synthetic Wheat dataset which has been created by a novel L-system, based on technological advances in cameras and deep learning. The dataset images have been automatically created, categorised, masked and labelled, and used to successfully train a synthetic neural network. This network has been shown to accurately recognise wheat in pasture images taken from the Global Wheat dataset, which provides for the ongoing interest in the phenotyping of wheat characteristics around the world. The proven Mask R-CNN and Detectron2 frameworks have been used, and the created network is based on the public COCO format. The research question is "How can L-system knowledge be used to create an accurate synthetic wheat dataset and to make cost-effective wheat crop measurements?".

Keywords: Synthetic Wheat · L-system · Global Wheat · Blender · COCO

1 Introduction

The strive towards improved wheat crop phenology is becoming increasingly dependent upon detection and recognition of anomalies by means of the analysis, synthesis, and training of available plant datasets [1, 2]. Public datasets such as the Global Wheat dataset [3] are few and far between and highlight the need for greater research and development of systems that allow for accurate detection of wheat head anomalies through synthetic methods. This paper introduces a novel measurement and dataset system using deep learning techniques. The paper uses the proven Mask R-CNN [4] and Detectron2 [5] frameworks in conjunction with a created network that is based on the public COCO format [6].

The paper assumes hardware advances in drones [7] and cameras [8], which hold the potential to significantly reduce the cost of current wheat measurement processes, and to assist with the creation of a global synthetic wheat dataset that can be applied to improved crop outcomes and a reduction in irregularities and costly variances.

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Synthetic wheat is defined by procedural rules and numerical parameters in an L-system as described in “The Algorithmic Beauty of Plants” [9]. Variations of these L-system rules and parameters define 3D models representing different global wheat varieties at their many growth stages. This allows a unified deep learning approach to worldwide wheat measurement, avoiding expensive manual capture and annotation of wheat images over multiple domains. The synthetic models would be combined in synthetic wheat datasets covering the multiple domains.

For each wheat domain, sample ground truth images of growing wheat would be captured in stereo. Matching individual L-system rules and parameters would be adjusted until the L-system produces realistic synthetic wheat plants for that domain. In this adjustment, the visualisation and processing of the synthetic wheat 3D models would be performed in open-source Blender 2.79 [10], which is a comprehensive 3D modelling and rendering framework chosen for this research. This research has used the Global Wheat dataset mono images [3] to represent the required domain ground truth.

To enable synthetic wheat visualisation, a novel interface has been developed to link an L-system to Blender. An L-system creates a file of “growth-steps”, which serves as a research record of the synthetic plants. Blender reads this file and grows plants in a 3D scene, allowing full animated visualisation and interaction.

Next, the animations are illuminated and photographed in stereo within Blender to produce realistic images comparable to the original real plant ground truth images. These synthetic wheat model images, with natural variations and growth stages, are used to train neural networks, which has been shown to accurately measure real wheat images for a chosen domain.

1.1 Deep Learning, Object Segmentation and Recognition

Deep learning has achieved accurate computer object segmentation and recognition which are used here for measurement of wheat crops. Deep learning is extraordinarily successful, but it has limitations in image processing according to [11]. These include the Pixel problem where small pixel changes in the input images can cause large errors in image recognition [12, 13], as well as the Picasso problem [14] where image parts can be jumbled in a similar manner to the misplaced eyes in a Picasso painting. In worst case scenarios the image background texture and colours can be incorrectly re-assembled and taken as a recognisable object. It is predicted that a new era of AI will remove current limitations and to understand object hierarchy [11].

A neural network limiting case was discovered and solved during research, whereby separate edges of several wheat heads were combined within a region to appear as a single wheat head. This is related to “CNN pooling”.

Recent developments in deep learning have improved object segmentation and recognition in images, and addressed the limitations and problems noted above. This project has chosen the successful region based convolutional neural network Mask R-CNN [4], and its successor Detectron2 [5]. The combination of Mask R-CNN and stereo images has been implemented [15–17] with the conclusion that the stereo method is far superior to existing non-stereo methods for object location and detection. The Mask R-CNN framework uses the standard Resnet101 backbone which was best for image recognition [1].

1.2 L-Systems: Theory, Practice, Application and Development

1.2.1 L-System Theory and Practice

An L-system is a mathematical theory of fine-grained plant and cellular development [9, 18, 19]. L-systems are described in detail in the book: *The Algorithmic Beauty of Plants* [9, 19], and they describe rewriting rules in an L-system based on the natural language grammar of the Backus-Naur production rules [20, 21]. L-systems demonstrate strong potential for realistic image synthesis [9]. This includes automatically evolving the L-system parameters for accurate synthesis.

An L-system holds knowledge of plant growth and its visible aspects as a set of procedural rules and numerical parameters and applies the rules to create a synthetic growing plant. These include externally defined mathematical surface and mesh objects representing leaves, flowers, textures, seeds, or grains [22, 23]. The positioning of each object in the created synthetic plant is controlled by the L-system.

In this paper an L-system is described, where the rules and parameters direct the growth of the stalk and the position, direction, and size of the grains of a wheat head, with Gaussian random variation about parametric means.

An L-system was developed with accurate knowledge of the hierarchy of the wheat plant since this knowledge is fundamental to real wheat recognition and measurement. Previous L-systems work [9] did not specifically cover wheat synthesis; and it was necessary to create a new approach to wheat synthesis. The system described here incorporates a new Python-driven L-system framework drawn from earlier work [24]. Each L-system rule represents the growth of a separate plant part and the higher plant structures at different growth stages. The set of rules forms an L-system algorithm which defines the synthetic plant appearance using contour diagrams and colour charts.

1.2.2 A Review of L-System Frameworks

The main frameworks supporting an L-system were reviewed, most notably L-studio [25], Virtual Laboratory [26], Open Alea's L-Py [27, 28], and Houdini FX [29, 30].

L-studio was the first framework applied to this research study. Whilst it was instructive in theory the L-studio was out-of-date in its materials file format, and application and investigation showed that it was a closed software system. Virtual Laboratory is a further derivative of L-studio. L-Py was out-of-date, but showed promise based on the revival work of Nikole Leopold [31]. Houdini FX was propriety and could not be run on the remote computer system chosen for this project.

Previous work on a modified L-Py framework from Python 2.7 to 3.6 demonstrated a removal of the dependency on the obsolete Plant-GL [31]. This adaptation of the L-Py framework became the chosen solution approach for this research.

1.3 L-Systems: L-Nap with Growth Steps and Blender Generated Graphics

1.3.1 L-NAP: A Novel Adaptation of an L-System

This research has invented a new Python L-system framework, that goes beyond the previous work of Leopold [31]. It uses a Python-only system to generate synthetic plants. Notably it generates images without the need to use the Leopold version [31] as part of the 18,000-line translation system integrated into L-Py.

This new Python L-system framework (described herein as L-NAP) incorporates a novel designed linking system, whereby a file containing "growth-steps" is created by this new framework and read by the Blender animation framework [10]. The benefit of the L-NAP L-system is its direct simplicity in using the Python language, whereby the user defines a Python function for each L-system rule, and the user programs the order of function calls to define the plant recursive growing structure. L-system parameters are defined and referenced from a global list. The L-system Axiom or start point is the main program. Each function logs its action, in the format of an encoded Python statement, representing a growth step with parametric values, to the linking file. These statements will be evaluated in Blender to visualise the plant growth.

1.3.2 L-System Benefits

Using the L-NAP framework it was revealed that an accurate synthetic wheat head could be defined by 20 L-system numerical parameters. This small number of parameters underlines the power of this L-system solution. The L-system parameters have been manually varied until the resulting synthetic plants were seen to visually match real plants. (See Fig. 1).

From these synthetic plant models, multiple 2D views of the wheat heads were automatically created by data pipelines and used to train a SPIN network.

1.3.3 L-System Printing of 3D Models and Visualisation

3D printed large scale synthetic models were created from object and material files exported from Blender [10]. Models were generated for demonstration purposes and to check authenticity against organic florae. Real plants were measured and studied to help develop synthetic plants. As part of an authentic approach involving synthetic models, a repeating grain pattern was measured, with unequal grains on each side of the wheat head.

2 Methods

2.1 Synthetic Plant Inference Networks: The Spin Methodology

The term "SPIN" refers to a Synthetic Plant Inference Network. The term is most broadly used to describe the past neural network creations using the Mask RCNN [4] and Detectron2 [5] systems which form a basis for the L-NAP framework for synthetic wheat plant models.

2.1.1 SPIN Networks

An important premise of this paper is that the accuracy of the SPIN network can be increased by adjustment of the L-system rules, parameters, and the Blender settings whereby the synthetic plants increasingly resemble real plant variations.

Large datasets are used to develop accurate neural network models for object segmentation and recognition models. For plant systems this can be significantly improved through an L-system as it will reduce the need for costly annotation. For example, the COCO image dataset of 80 classifications of common objects with approximately 2 million images required seven years to fully annotate [6].

This research has applied transfer learning to reuse the neural network of the extensive COCO dataset and has retrained it on synthetic wheat data to create a SPIN network. In this case the annotations of the data are performed automatically, at a significant cost saving, based on the topology of the known synthetic models.

A known criticism of Convolutional Neural Networks (CNN) is the problem of object recognition. The problem is most notably described as the inability to distinguish between a “flower and stem” using a CNN [32]. The L-NAP system provides a solution to better object recognition based upon the work of others in object recognition. This research has extended from the work of others [13, 33–36] in developing a solution to better object recognition by means of the inclusion of Capsules to store object relation information. Capsules are useful because they hold relational information by which a complex object can be understood. Capsules have inspired the present L-system solution. Capsules and L-systems are trying to resolve the same problem, namely the understanding of object hierarchy.

Drawing from these ideas the L-NAP system has been developed and shown to successfully train a neural network which can distinguish grains in a wheat head from wheat leaves and stems, as shown in Fig. 5.

2.1.2 SPIN Pipelines

Using SPIN pipelines, a method is described that allows for a creation of a neural network to emerge. The L-NAP system incorporates a Synthetic Plant Inference Network to establish an L-system that requires far less verification through expensive and time-consuming annotations. In the SPIN framework there are five data pipelines which are run consecutively, first to create synthetic plants using an L-system, and finally to train a convolutional neural network on automatically annotated views of these plants.

The **first** stand-alone pipeline implements an L-system which generates a linking file of plant growth-steps, for a chosen number of synthetic plants and for specific L-system rules and parameter settings.

The **second** pipeline is run in Blender, in foreground or background mode, and reads the linking file of plant growth-steps and exports numbered and grain-count labelled 3D models as object and material files.

The **third** pipeline is run in Blender, in foreground or background mode. It sets a scene with suitable Camera and Lamps, imports 3D plant models, takes photographs at various locations above the plants, and exports them as numbered and grain-count labelled view files in ping format.

The **fourth** pipeline makes use of metadata that is calculated from the view files, as wheat head bounding boxes and bit masks and summary files, in preparation for neural network training.

In the **fifth** pipeline SPIN models are trained from the image views created in the third pipeline and the meta data created in the fourth, using the CNN framework.

2.1.3 Research Objectives

The above methodology provides for three focal objectives. The first objective is to create a synthetic wheat dataset. The secondary objective is to provide a cost-effective wheat crop measurement using a trained dataset, and the third objective is to gather information that generates a crop knowledge database that can be referred to over time.

2.2 Predictive Crop Measurement Processes

The L-system knowledge structure has three processes.

Process 1: An L-system creates 3D plant models of crop plant types and stores a *model-map* of the model-number to model-characteristics. *Plant-network(s)* will be trained on 3D models.

Process 2: From drone images of the crop at known locations or on a flight path, the *plant-network*(s) will infer the synthetic models which best match the crop and store their information in the *crop-knowledge* base. There will be a separate network for each plant characteristic for improved accuracy and to allow distributed or multi-core processing. In cases where a *plant-network* overall inference score is not good then Process 1 will be rerun with adjusted L-system parameters to *evolve* a better *plant-network*.

Process 3: Crop *measurements* will be created from the *crop-knowledge* base. This creates an ongoing source that be referred to over periods of time to allow for decision-making and accurate inferences that form scientifically germane conclusions.

2.3 Domain Adaptation

Domain adaptation refers to transferring neural network knowledge from the trained network for one domain, to the network of a new domain, where plant varieties differ.

Differing plant varieties throughout the world can be represented by variations of the L-system rules and parameters, which is a robust approach to domain adaption. The adapted L-system would be run to produce new 3D plant models and the data pipelines would produce a new SPIN network for the new domain. It is considered that the robust transfer of adapted image pixel information between plant domains is ambiguous and open to interpretation [37].

2.4 A Higher Level of Accuracy

The L-system parameters were manually chosen so that the Blender models [10] visually resembled real plant images of the second domain of Global Wheat, which resulted in the following L-system models.

2.4.1 Created Synthetic Models

Views of synthetic models in simple poses using the Blender standard Camera and standard Lamps are shown in Fig. 2.

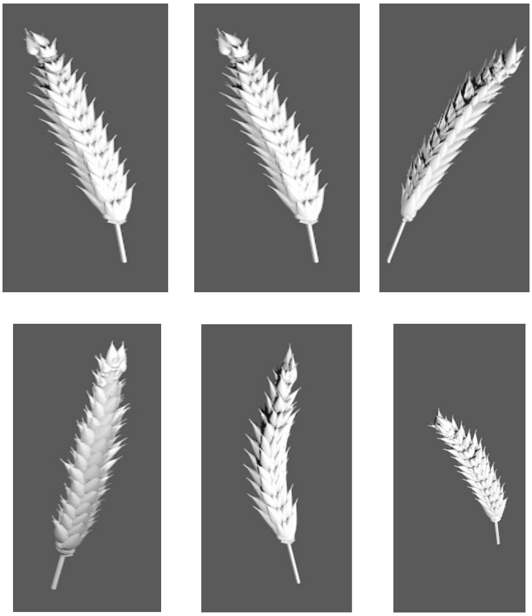

Fig. 1. Blender synthetic plant – side views

2.4.2 Creating Image Views – Blender: Camera, Lights and Action

The Global Wheat Dataset [2] has been used in this research for several reasons. Firstly, as the world's first large scale wheat head dataset, it represents a significant research instrument that is globally accepted and remains as a highly reliable collection that will provide for accurate training and comparative annotations for wheat heads around the world. In this research study, it was determined that the inclusion of a simple overhead camera and overhead lights setup, combined with random normal synthetic wheat growth variations, produced analogous wheat views to the Global Wheat dataset. In operational terms it was not necessary to specially position or orientate the synthetic wheat. Each wheat head was placed in a regular five by five square lattice under the camera and lights, which resulted in the images below. Using a camera and lighting set-up, the following example synthetic plant views, were created:

2.4.3 Creating Image Metadata

The image metadata was automatically calculated from the wheat images, as bounding boxes and masks as shown below. The captions of the boxed images indicate the known number of grain-rows present in the synthetic image, which when rounded to integer are the category of each training image. During synthetic neural network inference, the yield of a real wheat head can be estimated from the returned category of the synthetic best match.

Fig. 2. Illuminated synthetic plant top view examples

2.4.4 Specifications for Training Images

The bounding boxes and bit mask annotations are used to exactly specify the training images, to achieve the highest inference accuracy in the CNN. The annotations were automatically produced in a data pipeline. Note the range of grain-rows present in the training images, are shown in the captions as from 5.0 to 16.0. The final training of the CNN in this research project used 5,000 images.

Views and metadata are shown above. There were two hundred 3D synthetic models that were created by the L-system, with a normally distributed grain-row count from 5 to 16 (Fig. 3).

3 Result and Discussion

3.1 Results from Applying Spin Network to a Real Wheat Image

Using the SPIN network, we were able to train the synthetic neural network to accurately recognise real plants. This synthetic process was applied to the second domain of Global Wheat. Figure 4 displays a typical ground truth image.

The detection results, for the wheat heads shown in Fig. 4, can be visually recognised in Fig. 5. The caption "synthetic wheat" indicates that the network was trained only on synthetic wheat, and is being used to recognise real wheat, with IOU scores 70% to 99%.

Note that ground truth images were not directly used to train the synthetic neural network. Instead, a sample of ground truth images directed the setting of the L-system parameters, which through the SPIN data pipelines created synthetic images, which in turn trained the synthetic neural network.

3.1.1 Intersection Over Union

"Intersection over Union" (IOU) relates the area of the inferred or detected bounding box of the recognised real image to the area of the bounding boxes previously present during training on synthetic images. IOU is a quantifier recording the overlay for each projected class [38]. It can simply be described as Eq. (1).

$$\mathrm{IOU}_i = \frac{\text{Area of Overlap}}{\text{Area of Union}} \tag{1}$$

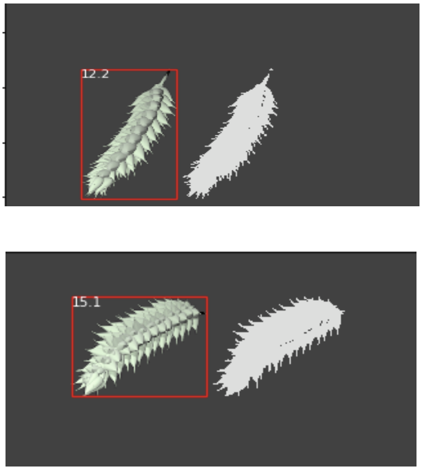

Fig. 3. Synthetic model views, masks, and bounding boxes with annotated grain row counts

Fig. 4. Global Wheat pasture image

3.2 Future Research and Development

3.2.1 Crop Measurement

Process 3 produces crop-measurements from the *crop-knowledge* base. This research project will aim to show accurate counting [39, 40] by the following hypothesis: Future development will investigate the way an L-system parameter such as a grain count on a synthetic plant is an accurate measure of the grain count of the real plant which matches that synthetic plant.

The crop measurements, such as grain count and colour, and classification would indicate plant health. The matched classification could indicate health or disease, and

Fig. 5. Detected wheat heads indicated by coloured bounding boxes

these would be counted and indicated to the user. In fact, the 3D model would be labelled with plant type, growth, health, coverage, and count indicators.

This project would discover the variety and usefulness of such synthetic plants, and the time taken to create them, and will attempt to classify these creations, [41] with relation to known plant taxonomies, starting with the laboratory plant data, and the drone images. The plant measurement accuracy will be compared for single image and stereo image neural network approaches.

3.2.2 Performance Measures

The *wheat networks* will be studied for accurate representation of real plants. This will be helped by listing the measurements in the *crop-knowledge base* to show how successful this network was in measuring real crops. The measurement accuracy will be compared with the published accuracy of similar projects. This proposal can be evaluated by comparing its inference accuracy to known datasets using Arabidopsis thaliana leaf counting., and to the inference results [42, 43] in the Global Wheat Dataset [3]. The evaluation parameters would be based on research.

4 Conclusion

This project has created a novel wheat L-system framework known as L-NAP which can automatically "grow" synthetic wheat plants with annotations, which closely resemble real wheat. These form a synthetic wheat dataset, for a chosen domain. The growth of the synthetic wheat is driven by only 20 numerical parameters, with adjustments simulating normal plant growth variations. This is important for wheat farmers because it enables the farming community to use technology through drones, sensors, and other mapping logistics to detect and respond to diseases in wheat, with weed recognition, optimised yields, and increased productivity.

Data pipelines have been implemented, whereby a neural network has been automatically created from the synthetic dataset using Blender and Deep Learning. This network successfully located and measured real wheat from pasture images of the training domain. This is important to wheat farmers because it allows agricultural and farming industries to visualise and conceptualise wheat production and wheat head optimization using simple software applications that make sense of L-system approaches.

The L-NAP framework enables a direct wheat knowledge transfer to other wheat domains, by adjusting the L-system numerical parameters. Thus, a synthetic wheat dataset and neural network, applicable to another wheat domain can be directly created. This is important to agricultural developments because it allows for the application of neural network optimisation to be readily applied beyond wheat and cropping, to include domain areas such as livestock, poultry, aquaculture, fisheries, in addition to crop-related agribusiness.

L-NAP demonstrates utility across agricultural domains through its ability to train a network to recognised objects (such as wheat heads) with a reduced reliance upon annotations and therefore an overall reduction in financial outlay. This research takes the existing L-systems research a step closer to commercial acceptance and implementation. The demand for synthetic image knowledge is crucial to broadacre grain farming. Data from drones and high-resolution camera imagery rely upon systems that can recognise and train networks for the benefit of crop phenology and productivity.

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