The 3-dimensional Plant Organs Point Clouds Classification for the Phenotyping Application based on CNNs.

Kanittha Rungyaem
Kasetsart University, Bangkok, Thailand
kanittha.rungyaem@gmail.com

Kanjanapan Sukvichai
Kasetsart University, Bangkok, Thailand
fengkpsc@ku.ac.th

Teera Phatrapornnant
National Electronics and Computer Technology Center, Thailand Science Park, Pathumthani, Thailand
teera.phatrapornnant@nectec.or.th

ABSTRACT

The rice breeding produces the high-throughput via a genotyping technology. It can rapidly test and analyze on a large number of samples while the performance of phenotypic evaluation is still very low because of the manually evaluation. Therefore, this is the main barrier retarding the new rice varieties development. This research is aimed to develop a method for classifying plant organs from 3D point cloud in order to analyze plant morphology or architecture automatically. The rice plant was scanned with a 3D laser scan machine. The points in the cloud were reduced by the skeleton skimming method because the number of points in each cloud group is too large. Thus, it is necessary to preprocess before importing into neural networks for classification. The PointNet was selected as the 3D classifier in this research. The first experiment was conducted in order to evaluate the proposed method. The result showed that the proposed method can classify rice organs, regardless of rice varieties, with accuracy of 87.04%. Then, the second experiment was conducted in order to obtain the accuracy of the network for each rice variety to demonstrate the influence of rice cultivars in the classification due to their different shapes. The results showed that the SPRLR, which had large numbers of leaves and yield, has the lowest accuracy of 51.61% while the other varieties with the greater leaf and panicle distribution have a much better accuracy. The Nieow dum had 91.16% accuracy while Jae hwa, Kaow lueng and Kam had 89.06%, 86.52% and 75.22% accuracy respectively.

CCS CONCEPTS

• Computing methodologies; **• Artificial intelligence**; **• Computer vision**; **• Computer vision problem**; **• Image segmentation**;

KEYWORDS

3D Data, Point Cloud, Classification

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1 INTRODUCTION

Climate change has significant impact on agriculture sector. This leads to the decrease in crop productivity while the demand for food and energy are increasing dramatically in the next decade. To mitigate the abiotic and biotic stresses affecting on the crop growth and yield [1], the development of the new plant type that can be tolerant to the severe environment and resistant to the new plant insects and diseases is required. In the process of plant breeding, plant breeders are required to collect samples and record large amounts of plant data in order to understand the plant morphology. It is important for the plant phenotype study [2], for example, the development of new rice varieties is required to assess plant traits, e.g., leaf width, plant height, leaf color, leaf area, which may be impact from diseases or abiotic stress. Current rice breeding has the high-throughput genotyping technology. It can rapidly test and analyze on a large number of samples while the performance of phenotypic evaluation is very low because of the manual evaluation. Therefore, this is the main barrier retarding the new rice varieties development.

Therefore, the non-destructive, robust and automatic analysis of plant data is introduced by Paproki [3] which uses the 3D laser scanning to capture various plant parameters under controlled conditions. The important information of the plant architecture is a plant dimension, specific organs and organs volume which can be obtained from the 3D structure of plants. Thus, the requirements for an implementation of phenotyping process are fulfilled. The automatic 3D phenotyping recognition is based on plant's 3D point clouds data.

Aim of this research is to develop an automate plant organs classification method. This research focuses on the rice plant because rice is the economic crop and basic food for Thai people. By scanning the rice plant with laser scanner, the 3D point cloud image of the rice plant is obtained and shown in Figure 1. A point cloud is a set of data points scattered in 3-dimensional space to represent a shape or object. Each point has its own of X, Y and Z coordinates. Since the point clouds is an unstructured file, thus, each point only collects the (x, y, z) coordinate that was scanned from the laser scanner [4]. Point cloud are generally produced by laser scanner. In this research used Red Line Laser module (TYS650-L) to generate point cloud of rice plant. This Red Line Laser module is fully self-contained with laser diode, integrated laser driver circuit and glass lens optics, generating a better line quality and better power

Figure 1: Laser scanner machine.

Table 1: Specifications of TYS650-L

Laser Class	II (2), IIIa (3R), IIIb (3B)
Wavelength	650nm
Output Power	<1mW, 5mW,20mW, 50mW, 100mW
Operation Voltage	3V DC
Operation Current	30mA
Operation Temp	-10C to +40C
Optics	Glass lenses
Divergence	0.1-0.6 mrd
Beam	Line (90 degrees fan angle)
Length	70 mm
Diameter	16 mm
Wires Length	100 mm
Case Material	Aluminum

stability. Specifications of the laser scanner shown in Table 1. Laser scanner beam a horizontal line to scan the rice plant. The result is a point cloud of rice plant as shown in Figure 1

In order to classify the phenotype of rice plants, this research purpose the automate deep learning method for the point clouds information. Since the rice point cloud has many leaves and stalks overlap. For that reason, it is difficult to separate the organ of rice plant, Therefore, the data preprocessing must be performed before the point cloud can be classified. Point cloud of rice plant was used to data preprocessing by using the skeleton of the rice plant to segment the point cloud into sub-sets of point cloud before using in the network. PointNet had been chosen as the main network.

2 DATA PREPROCESSING

There are many points in the rice's point cloud, at least 100,000 points per plant, it will take more time to calculate and teach the network if the whole rice's cloud is fed into the classifier. Thus, the preprocessing step is required to reduce the points but if the number of points in cloud were reduced too much in the preprocess step, the shape of the rice plant will be changed and it is difficult to identify the plant organs. In order to take care of this issue, the point cloud for each rice branch was separated by using the skeleton technique and each branch will contain less points. The overall preprocessing steps are explained in Figure 2

The processes to obtain the skeleton of rice plants were introduced by Cao J [6], Wu s [7] and Jayadevan V [10]. The first step is to select the point $(x,\ y,\ z)$ from the top of the desired rice leaf defined as $(x_0,\ y_0,\ z_0)$. Next is to create a sphere of radius r_1 with center of sphere is $(x_0,\ y_0,\ z_0)$. Then, the intersection between the sphere and the main point of the rice plant P_0 can be found. The intersection in this case is also be a small group of the point cloud which is called P_1. Next step is to find the center of mass $(x_1,\ y_1,\ z_1)$ from the mean of the coordinates $(x,\ y,\ z)$ in the point cloud P_1 and use this point $(x_1,\ y_1,\ z_1)$ as a starting point for a straight line of length r_2 and having the same directional radius as the vector with beginning point $(x_0,\ y_0,\ z_0)$ and last point $(x_1,\ y_1,\ z_1)$. At the end

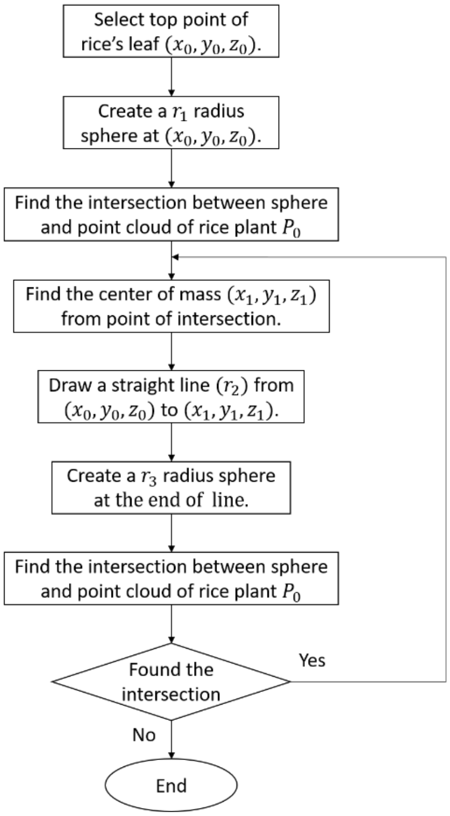

Figure 2: Flowchart shows the process of making the skeleton of the rice plant

Figure 3: Results of finding the skeleton of rice leaves

of the straight line creates a sphere of radius r_3. After that, the process is repeated in order to find the intersection between the sphere and the main point of the rice plant P_0. Which are group of small point cloud P_2. Find the center of mass $(x_2,\ y_2,\ z_2)$ from the mean of the coordinates $(x,\ y,\ z)$ in point cloud P_2 and use it as a point of skeleton as shown in Figure 3. By following the steps as shown in Figure 2, therefore, the skeleton of the rice plant is obtained as shown in Figure 4. The skeleton result shows that it contains a clear the rice plant structure and it is easy to be classify.

From the process of finding the skeleton of the rice plant, the N point clouds, P_N, are obtained. Each point cloud has a different number of points. Therefore, before importing to the neural network for classification, the number of points must be adjusted to be the same in order to control the dense of each cloud. In which if the number of points is greater than the specified number, N, the random number of N points will be generated. But if the number of points is less than N, it will bring the points close to each other to the midpoint between the points to increase the number of points as needed.

3 CONVOLUTIONAL NEURAL NETWORKS

Point cloud is an unordered set of vectors as seen from a data structure point of view, unlike pixel array in images, therefore, PointNet is the appropriate network for this research. PointNet, proposed by Qi C [5], was the initial approach for novel type of neural network that directly consumes unordered point clouds, which also takes care of the permutation invariance of points in the point cloud. PointNet can be used for object classification, parts segmentation, and scene semantic parsing. PointNet is robust network for the input perturbation and corruption. Also, the network can learn to summarize a shape by a sparse set of key points. The PointNet is shown in Figure 5

The classification network takes n points as the input because input of the network is point in the point clouds which are (x, y, z) coordinate. The classification network uses a shared multi-layer perceptron (MLP) to map each of the n points from three dimensions (x, y, z) to 64 dimensions. This procedure is repeated to map the n points from 64 dimensions to 1024 dimensions. Because each of the n input points are represented as a vector and are mapped to the embedding spaces independently. The input transform and feature transform block in the network use T-Net. T-net is mini-network to predict an affine transformation matrix and directly apply this transformation to the coordinates of input points. With the points in a higher-dimensional embedding space, max pooling is used to create a global feature vector without losing important information. Finally, a three-layer fully connected network is used to map the global feature vector into k output classification scores.

4 EXPERIMENTAL RESULTS

4.1 The training models

The dataset used to train model was panicles point cloud and leaves point cloud, which are separated from the rice point cloud as shown in Figure 6. Since this research wanted to measure panicle and focus on separating the rice from the stems and leaves. In addition, the leaves and stems of the rice plant are very similar. Therefore, the classes are defined as two classes. There are panicles and leaves by combining the stems and leaves of the rice plant together. The number of panicles and leaves used for training and testing is 1000 set and 100 set respectively. The result of testing is depicted as a confusion matrix in Figure 7 and model accuracy in Figure 8

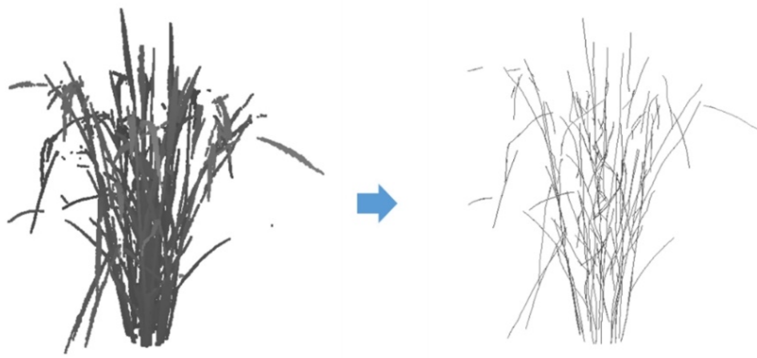

Figure 4: Skeleton of rice plant

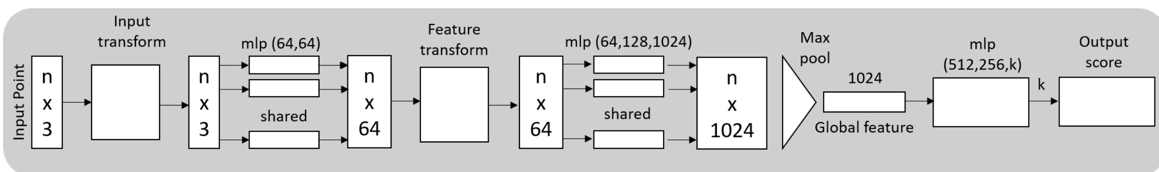

Figure 5: PointNet Architecture for Classification Network

Figure 6: (a) Panicles and (b) Leaves are used to train the model

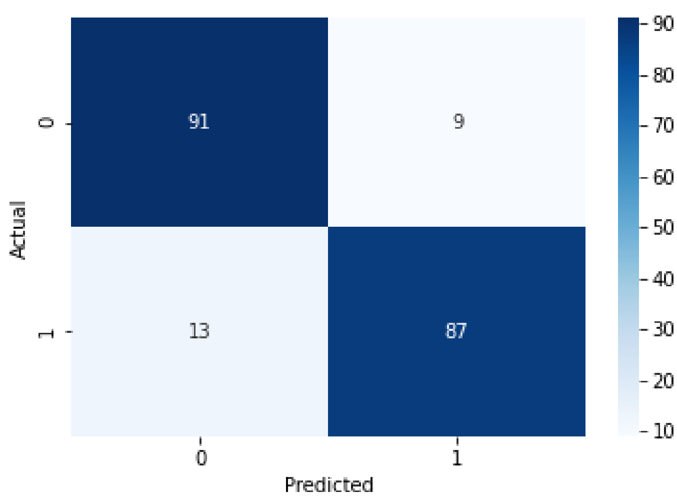

Figure 7: Confusion matrix of applying PointNet to classify rice organ

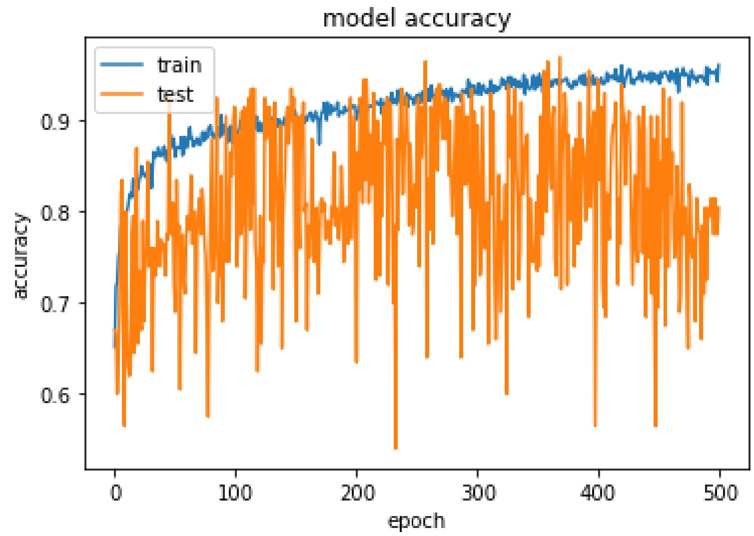

Figure 8: Model accuracy

Table 2: The accuracy of the network

Plant	Actually Panicles	Predicted Panicles	Accuracy
Rice	656	571	87.04%

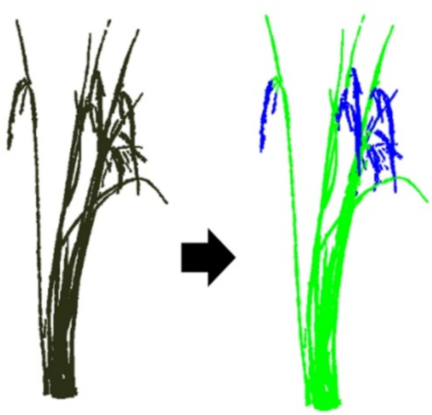

Figure 9: The result of network

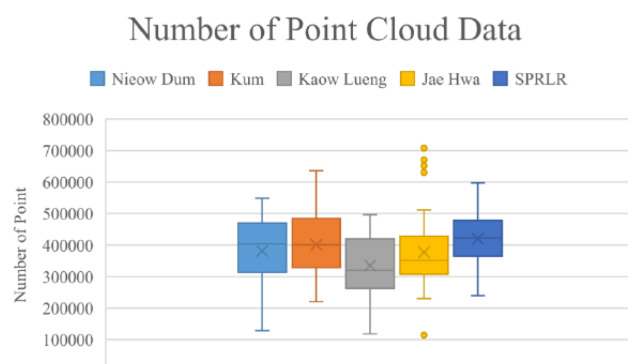

Figure 10: The graph shows the number of rice point cloud for each variety

4.2 The experiment on predicting panicles

The experiment was performed by putting the rice's point cloud that are separated by skeleton into the network as the input. The point cloud of the rice plants used in this experiment was randomized from 100 rice plants. The rice varieties used in this experiment are Nieow dum, Kam, Suphan, Tong Banla, PTT, Chai Nat, Kaow lueng, Ipo, Jae hwa and SPRLR. The network will predict and label group of point for the specific class or rice organ which are shown in Figure 9. The accuracy of network can be obtained by comparing the number of the ground truth which labeled manually and the result of the proposed method. The result shows in the Table 2

4.3 The experiment on plant varieties

The second experiment was conducted by separating the rice data and grouping data according to each rice varieties. The varieties of rice plants which are Nieow dum, Kam, Kaow lueng, Jae hwa and SPRLR. There are 50 plants per varieties. that were selcted for

Table 3: The number of rice varieties

Rice varieties	The number of rice varieties	The number of Point cloud	The number of panicles
Nieow dum	50	19,043,230	226
Kam	50	20,046,989	236
Kaow lueng	50	16,737,657	322
Jae hwa	50	18,870,126	240
SPRLR	50	21,007,655	355

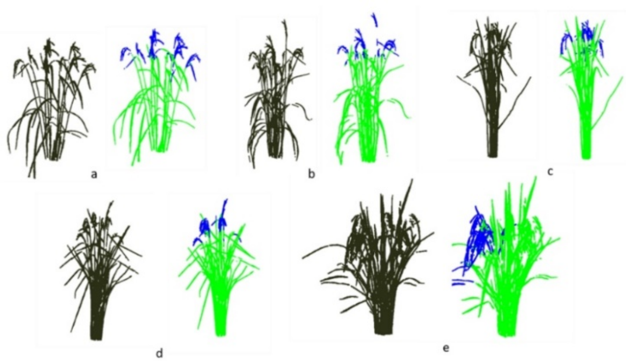

Figure 11: a) Nieow dum b) Kam c) Kaow lueng d) Jae hwa e) SPRLR

Table 4: The accuracy of each variety

Rice varieties	Accuracy
Nieow dum	91.16%
Kam	75.22%
Kaow lueng	86.52%
Jae hwa	89.06%
SPRLR	51.61%

this experiment since these rice varieties are the most popular rice varieties in Thailand. The number of rice varieties were tested, that are shown in Table 3 and the number of points for each varieties is shown in Figure 10. The result shows in Figure 11. The accuracy of each varieties is different and shows in Table 4

5 CONCLUSIONS

This research proposed the classification technique for rice organs based on the convolutional neural network approach called the PointNet. The rice plants were scanned using the 3D scanner then the rice point clouds are the input data for the classifier. The pre-processing is required to reduce the number of points in each cloud. In order to maintain the same quality data set, then, the skeleton technique is used. The preprocessed rice skeletons were fed into the PointNet for learning. Rice organs in 3D were labeled and used as the prediction ground truth for generating loss function of the network. After trained, the network showed the good result. To find the accuracy of the network, the number of correct outputs from network is counted by conducting experiments. In the first experiment, all rice varieties data were used as the input for the network and the overall accuracy of the classified network for the rice organs are determined. The result is 87.04% accurate. Then the second experiment is conducted for specific rice varieties in order to obtained influences from rice varieties to the organ classification network because the shape of the rice plant organs from different varieties are different. The experimental result shows that the SPRLR varieties, which has large overlap of leaves and spines, has the lowest accuracy of 51.61% while the other varieties with greater leaf and yield distribution have a much better accuracy. The Nieow dum has the most accuracy of 91.16% while Jae hwa, Kaow lueng and Kam have 89.06%, 86.52% and 75.22% accuracy respectively.

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