Comparison of 3D Rice Organs Point Cloud Classification Techniques

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***Abstract*— The performance of phenotypic evaluation is a hurdle in the rice breeding process. Because of manual evaluation, the traditional evaluation procedure is very slow. Therefore, this is the primary impediment to the development of new rice varieties. The focus of this research is to compare techniques for categorizing plant organs using 3D point clouds so that plant morphology and structure can be analyzed automatically. A 3D laser scanner was used to scan the rice plant and create the rice plant point cloud. The point cloud of the rice plant contains the rich information due to the enormous points in the cloud cluster. Therefore, the number of points in each cloud must be minimized via skeleton preprocessing technique before can be used for training the network. The skeleton approach is used to thin the cloud while keeping the vital information intact. We suggested two approaches for classifying rice organs in this study. Tensor-based classification is the first method. The second technique is PointNet. In comparison, the PointNet was the most successful for classifying rice organs and spent the least amount of time.**

Keywords—3D data, Point Cloud, Classification

I. Introduction

Agriculture is adversely affected by climate change. Concerns about the agronomic consequences of climate change motivate academics to perform studies to improve existing plans and address emergent concerns. Because agriculture and the agricultural system are projected to be impacted by climate change such as rainfall is insufficient for plant growth, and extreme occurrences such as droughts, floods, and wind storms have become more and more severe [1]. For this reason, Climate change adaptation seems to be a challenging breeding challenge. The challenge is exacerbated by the fact that temperature and rainfall have an impact on the distribution, growth, and survival of crop diseases [2].

Plant breeding is a method of modifying and improving plant varieties to meet specific needs. It is essential to develop and maintain sustainable agriculture. Breeding is necessary to develop resistance to diseases and pests [3]. The selection of desired plant characteristics, also known as phenotyping, is an important step in improving the development of new plant varieties in plant breeding processes [4]. Plant breeders must gather samples and record vast quantities of plant data in order to assess the advantages and disadvantages of various plant types. That is a difficult, tedious, and time-consuming process. An additional drawback is that plant samples in the experiment are often damaged during measurements. This has a detrimental impact on monitoring plant progress during the growing season. Therefore, high throughput, high precision and low-cost phenotype analysis is urgent. Recent advancements in image-based 3D generation offer the opportunity to create high throughput phenotypes.

A non-destructive, resilient, and automated plant data analysis is critical in creating phenotypes so that plant development is not hampered, and experimental specimens are not destroyed. The 3D laser scanner is the answer to this issue. In this research, 3D laser scanner uses to scan and create the point cloud of rice. It is feasible to estimate the three-dimensional structure of plants in order to get the most relevant plant architectural information, which includes the plant's dimension, organ volume, and particular organs. Consequently, the conditions for the execution of the phenotyping procedure have been met. The plant's point clouds data is used to automate 3D phenotyping categorization.

The aim of this research is to evaluate and contrast automated 3D rice plant organ classification approaches in order to determine the optimum method for classifying rice organs. Because rice production accounts for a large amount of Thailand's economy and rice is the Thai people's main meal, this study concentrates on the rice plant.

II. Data Acquisition and Labeling Process

A. Data Acquisition

Point cloud is a collection of numerical data that depicts the location of a single point in space. The TYS650-L red line laser module was used to create point cloud as shown in Fig. 1.

Fig. 1. TYS650-L (Red Line Laser Module).

B. Labeling Process

In 3-dimensional space, a point cloud is a collection of data points that are spread to depict a form or object. Each point is identified by its unique set of X, Y, and Z coordinates. The rice plant has at least 100,000 points per plant. That makes the rice plant contain huge amounts of data. Calculating and teaching the network will take more time and need a large amount of memory. Therefore, preprocessing is critical for minimizing points. However, If the number of points in the point cloud is lowered significantly, the geometry of rice point cloud is lost, making rice organ separation more difficult. To solve this problem, the point cloud was segmented into branches, and each rice branch was isolated using the skeleton approach. The result was that each branch generally had fewer points, as shown in Fig. 2.

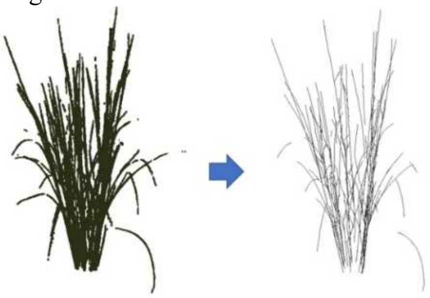

Fig. 2. Skeleton of a Rice Plant

Creating a rice plant skeleton to serve as a label for the point cloud was introduced by Wu S [5], Cao J [6], and Jayadevan V [7]. There are 5 steps for this algorithm, as shown in Fig. 3, and each step is explained as follows:

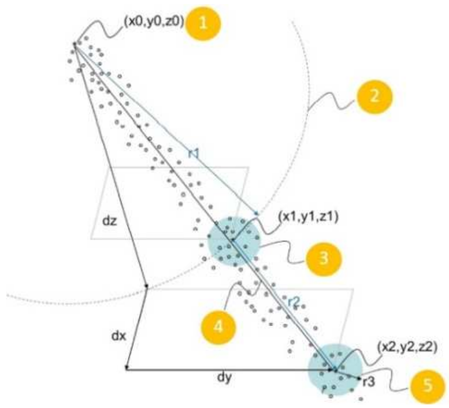

Fig. 3. The process of making a rice branch skeleton.

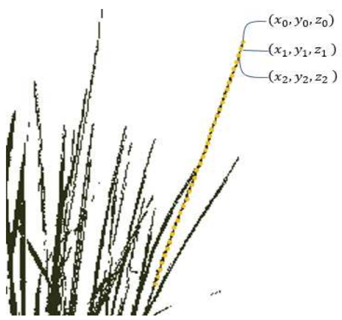

Fig. 4. Finding the skeleton of rice leaves produced the following results.

1) Choose the top position (x_0, y_0, z_0) of the desired rice leaf.
2) Create a sphere of radius r_1 and a center of (x_0, y_0, z_0). After that, identify the intersection of the sphere with the main point of the rice plant, represented by P_0. It is composed of a short series of data points that define the point cloud's intersection (P_1).
3) Using the average of the coordinates, we can identify the center of mass (x_1, y_1, z_1) in the point cloud P_1 and computing the average of the coordinates. The point (x_1, y_1, z_1) with the same directional radius as the vector's beginning and ending points should be used as the starting point for a straight line of length r_2.
4) A sphere of radius r_3 has been formed at the end of the straight line. The method is then repeated to locate the place where the sphere and the primary point of P_0 intersect. P_2 is a collection of tiny point clouds.
5) Calculate the center of mass (x_2, y_2, z_2) in point cloud P_2 by averaging the coordinates (x, y, z). Using the point cloud P_2 as a skeleton point, the skeleton of rice plant is created as seen in Fig 4. The skeletal analysis demonstrates that the structure of rice plants is different and easy to categorize.

III. Proposed Methods

A. Tensor-based classification

Clustering is one of the major data mining techniques for discovering information in huge datasets, according to DBSCAN [8]. This approach might be used in a variety of disciplines. It divides data objects into groups based on a similarity metric. DBSCAN is a well-known unsupervised technique for segmenting big point sets with arbitrary dimension. The DBSCAN technique effectively finds "core points" inside a set, where the core points are given by two parameters: a distance value that determines the search radius around each point, and the minimal number of points, minPTS, that must exist within a 'core.' As seen in Fig. 5, adjacent core points are then combined to create a cluster.

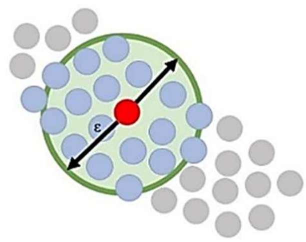

Fig. 5. Search points for the DBSCAN algorithm.

The first and second tensors of point cloud are used to encode local point characteristic in relation to their surroundings in order to categorize the point cloud of the rice plant [9]. Tensors are generalizations of scalars, vectors, and matrices to an arbitrary number of indices, where scalars are zero-rank tensors that contain a single number, vectors are first-rank tensors that contain magnitude and direction, and matrices are second-rank tensors. In this research, t_i are the first-or tensor, x_i are the core point, and x_j is the neighbor's points:

$$t_i = [t_x \; t_y \; t_z]^T = \sum_{j \in \sigma} (x_i - x_j) \tag{1}$$

T_i are the second-order tensor at σ as the neighborhood of x_i:

$$T_i = \sum_{j \in \sigma} (x_j - x_i) \otimes (x_j - x_i) \quad (2)$$

$$T_{3\times3} = V\Lambda V^T = \sum_{i=1}^{n} \lambda_i v_i v_i^T \quad (3)$$

Fig. 6. illustrates an orthonormal matrix generated by the concatenation of eigenvectors formed by a non-negative diagonal matrix comprised of its eigenvalues. In this case, $\Lambda = diag(\lambda_1 \lambda_2 \lambda_3)$ is a non-negative diagonal matrix made of its eigenvalues.

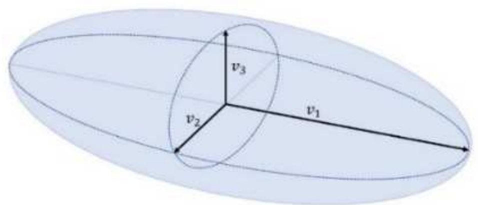

Fig. 6. Graphical representation of Eigenvectors.

For the eigenvalues and eigenvectors classification, this research uses K-Nearest Neighbors (K-NN), Decision Tree, and Random Forest. These algorithms are the popular neural networks for classification of huge amounts of data.

K-NN is a classification data by comparing the data of interest against other data that is similar or not based on a distance metric. The majority vote of the K closest instances is output as the input observation classification result.

Decision Tree is a statistical method of decision-making. It looks like an upside-down tree. Within the tree, there are nodes that make decisions. The branches of the tree are the results obtained from the experiment. And where leaves are groups of information at the bottom is the answer to the decision.

Random Forest is a kind of classifier that uses many decision trees in different subsets of a given dataset and aggregates the data to boost the predictive accuracy of that dataset rather than relying on a single decision tree to make predictions about it. The random forest algorithm creates a forecast result based on the majority vote of each tree's outcome in this study, which is then utilized to construct the final prediction.

B. *Classification Network PointNet*

In contrast to picture pixel arrays, a point cloud is a data structure representation of an unordered collection of vectors. Therefore, this research requires the use of the PointNet network. The original method for creating a novel kind of neural network, suggested by Qi C [10], was PointNet. The PointNet architecture is shown in Fig. 7.

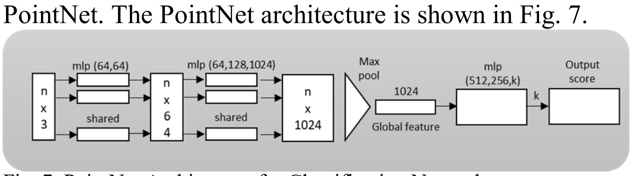

Fig. 7. PointNet Architecture for Classification Networks.

The two primary components of PointNet are as follows:

1) *Multi-Layer Perceptron (MLP)*

The Multi-Layer Perceptron is a kind of feed-forward neural network that complements the feed-forward neural network. The multi-layer perceptron is a function in the PointNet network for feature extraction and information dimension conversion. MLPs are used to map the input points to a higher-dimensional space in a consistent manner. It is the process of continuously optimizing the weight vector and offset, as well as calculating the right weight and offset values, in order to get the best feature extraction.

2) *Max Pooling*

In the max pooling section of PointNet, the max pooling uses the symmetric function because the point cloud is made up of unstructured data and numerical sets. So, the information of the item is determined by its relative position, and the sequence of the points has no bearing on the information represented by the point cloud data. Therefore, PointNet has to use the symmetric function with max pooling.

IV. Experimental Result

A. *The models for training.*

Since we used a skeletal technique to label the point cloud. The point cloud of rice was divided along the branches of the rice plant. The point cloud of rice plant is utilized to create the train model, which is then disconnected from the rice plant using the MeshLab program, as illustrated in Fig. 8. Because the purpose of this study was to determine panicle yield and to isolate the rice from the stems and leaves, it was important to discriminate between the yield and the stems and leaves. Additionally, rice leaves and rice stems are remarkably similar. As a consequence of this, the classes are split in two classes. Panicles and leaves are generated by merging the stems and leaves of the rice plant. Training and testing were conducted using 1000 panicle sets and 100 leaf sets.

Fig. 8. Panicles (a) and rice leaves (b).

In this training, K-NN, Decision Tree and Random Forest algorithm were used for rice organ classification based on two feature sets, i.e., 1) eigenvalues $(\lambda_1, \lambda_2, \lambda_3)$, 2) eigenvectors (v_1, v_2, v_3). Panicles and leaves are used in 1000 and 200 sets, respectively, for training and testing.

TABLE I. Confusion Matrix of Applying Tensor-Based Classifcation (K-NN)

	Panicles	Leaves
Panicles	64	136
Leaves	12	188

TABLE II. CONFUSION MATRIX OF APPLYING TENSOR-BASED CLASSIFICATION (DECISION TREE)

	Panicles	Leaves
Panicles	104	96
Leaves	29	171

TABLE III. CONFUSION MATRIX OF APPLYING TENSOR-BASED CLASSIFICATION (RANDOM FOREST)

	Panicles	Leaves
Panicles	89	111
Leaves	9	191

TABLE IV. CONFUSION MATRIX OF APPLYING POINTNET

	Panicles	Leaves
Panicles	178	22
Leaves	10	190

B. *The Panicle Prediction Experiment.*

The experiment was conducted by loading the rice point cloud into the PointNet after it had been segmented by skeleton. The skeleton technique was utilized in part of tensor-based classification to separate the point clouds of rice plants prior to DBSCAN clustering and to create the first and second tensors for computing the eigenvalues and eigenvectors of each group point cloud. The point cloud for this experiment was created using a random sample of 100 rice plants. This experiment used the rice varieties Ipo, Jae-hwa, Kaow-lueng, Korkhor, Kum, Nieow-dum, PTT, Saibua, Samoe, and Tom-luang. The networks will forecast and identify a collection of points for each rice organ or class shown in Fig. 9. The accuracy of networks is determined by comparing the output of the proposed technique to the number of manually labeled ground truth samples. TABLE V and TABLE VI reveal the results and time required to forecast the rice organs.

TABLE V. THE ACCURACY OF EACH NETWORK

Method	Actually Panicles	Predicted Panicles	Accuracy
K-NN	660	278	42.12%
Decision Tree	660	342	51.81%
Random Forest	660	381	57.72%
PointNet	660	584	88.48%

TABLE VI. TIME TO PREDICT THE ORGANS OF RICE PLANT

Method	Running Time (second)
K-NN	45
Decision Tree	46
Random Forest	47
PointNet	13

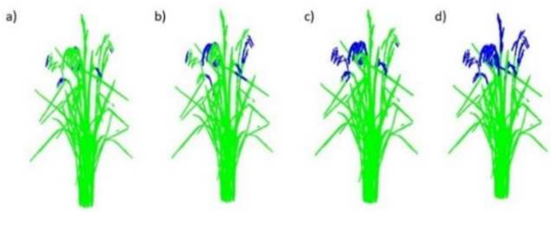

Fig. 9. Shows the outcomes of a) K-NN, b) Decision Tree, c) Random Forest, and d) PointNet.

V. CONCLUSION

The classification approaches employed in this study for rice organs are tensor-based classifications and the PointNet technology for convolutional neural networks. The rice plants were scanned using a 3D scanner, and the rice point clouds supplied as input data for the classifier. Preprocessing is required to keep the number of points in each cloud to a minimum. The skeleton technique is used to maintain the same level of data collecting quality. To aid in learning, the PointNet was extended to incorporate the skeletons of preprocessed rice. As part of tensor-based classification, the point cloud of a rice plant must be clustered by determining the cloud's eigenvalues and eigenvectors using DBSCAN. Rice organs were 3D-labeled and utilized as the loss function prediction ground truth. To determine the network's accuracy, the number of accurate outputs was counted. The experiment utilized rice data as the input for the networks and assessed the classification network's overall accuracy for rice organs. From these four techniques, PointNet is the best classification network. PointNet has an accuracy of 88.48 percent and is the quickest approach. Predictions take on average roughly 13 seconds.

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