

PLANT RECOGNITION USING STEREO LEAF IMAGE USING GRAY-LEVEL CO-OCCURRENCE MATRIX

¹Hermawan Syahputra, ²Agus Harjoko, ²Retantyo Wardoyo and ²Reza Pulungan

¹Department of Mathematics, Faculty of Mathematics and Natural Sciences,
State University of Medan, Medan, Indonesia

²Department of Computer Science and Electronics, Faculty of Mathematics and Natural Sciences,
Universitas Gadjah Mada, Yogyakarta, Indonesia

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ABSTRACT

Adequate knowledge, such as information about the unique characteristics of each plant, is necessary to identify plant. Researchers have made plant recognition based on leaf characteristics. The leaf image-based plant recognition in view of different angles is a new challenge. In this study, the research on the plant recognition was conducted based on leaf images resulted from 3D stereo camera. The 3D images are very influential in the development of computer vision theory, which can provide more detailed information of an object. One of the information that can be obtained is about the position of the object in its image with the background as well as of the camera. One of the ways used to obtain such information is to calculate the disparity. However, this method will only tell the position of the object compared to other objects without that of range. Sum Absolute Different (SAD) is a method that can be used to find the disparity value. The SAD method does not require heavy computations and long process. Before calculating the disparity, all the images should be previously segmented. The objective of this segmentation is to separate all the objects from the background. Furthermore, filtering and polynomial transformation at the results of disparity is necessary to improve the quality of resultant images. Furthermore, 22 features were extracted using GLCM features (second order statistics) of images resulted from disparity improvement. The highest accuracy of match in the recognition of plant varieties was obtained at 50 cm distance and in the recognition of three plant varieties was 83.3%.

Keywords: Disparity, Plant Recognition, Stereo Vision, GLCM

1. INTRODUCTION

This The recognition of plants is very important to study the genetic diversity of plant (Singh *et al.*, 2011; Lu *et al.*, 2012), ecological sensitivity, environmental durability, the maintenance of atmospheric composition, nutrient cycle and other ecosystem processes (Du and Wang, 2011). Some researchers developed the recognition of plant to manage food production (Wu *et al.*, 2009), to recognize medicinal plants (Ershad, 2011; Pornpanomchai *et al.*, 2011a), to manage and control the growth of plants (Chuanyu *et al.*, 2011) and to meet the objectives of research in the field of botany. In addition, the recognition of plants can also be used to identify and control pests and plant diseases (Hashim *et al.*, 2010) and so on.

Sufficient knowledge is required to identify the plants such as knowledge or information about the unique characteristics of each plant. The characteristics of plants can be obtained through the structure of plant organs, such as stems, leaves, flowers, seeds or other structures. However, many researchers do plant recognition based on leaf characteristics (Wu *et al.*, 2009; Singh *et al.*, 2010; 2011; Pornpanomchai *et al.*, 2011b). This is because the leaves of plants are more easily obtained than others. Fruits and flowers on the plant cannot be obtained from plants.

Leaf-based plant recognition is so far a difficult task, mainly for those with irregular shapes. Some leaf images from one of the plant varieties captured by the camera do not always produce the exactly same shape and position.

Corresponding Author: Hermawan Syahputra, Department of Mathematics, Faculty of Mathematics and Natural Sciences, State University of Medan, Medan, Indonesia

Moreover, the plant leaves that are the 3D objects appear as the 2D objects if they are captured by a regular camera, so that extraction of the features of 2D images does not directly correspond to the object model. This led to the possibility of errors in identifying the plant leaves. Therefore, a method is required to provide a more detailed description of the images corresponding to the original object. The transformations of 2D to 3D or 2D to 3D images should be done before the features are observed and matched with the 3D object model. To retain the features of an object from different positions is very difficult. Researcher believes that study in the recognition of plant based on leaves can be developed using the resultant images of leaves captured by the 3D camera, so it can improve the ability and accuracy of recognition.

1.1. Preliminaries

1.1.1. Stereo Vision

Stereo vision is an attempt to get the stereo images of object from two different positions. The stereo images are obtained by placing two cameras in the same field with a certain distance or using a camera with two lenses (stereo camera).

1.2. Disparity

The types of 2D or 3D images are very influential in the development of computer vision theory to construct a system that can provide information about an object. One of the information that can be given is the position of the object in the image with a background and of the camera. One of the techniques that can be used to obtain this information is the calculation of disparity or just called as disparity.

Disparity is a component of the stereopsis process, indicating the difference of an image captured by left and right eyes. It is obtained by comparing a stereo image that overlap with other images in turn. The stereo images are two images taken from the same object using two cameras with a certain distance or a camera with two lenses in a certain distance, which usually has a distance equal to the distance of two human eyes.

The method used to find out the disparity value is the Sum of Absolute Differences (SAD). This method does not require a lot of computations and a long process, though the calculation speed also depends on the specifications of computer used. To estimate the difference, the process selects the same values of comparative operations between two images (Kamencay *et al.*, 2012).

The idea of disparity can be illustrated in **Fig. 1**, where an arbitrary location of the point P in three dimensions is considered as a distant object seen by two

cameras that are positioned in the same orientation but separated by a distance called the baseline. Furthermore, the object will appear in the same position in the two stereo images. Distance between the objects in the left and right images known as d disparity is defined by Equation (1), where x_L and x_R are the x coordinates of projection for the 3D coordinates into the left and right field of I_L and I_R images (Kamencay *et al.*, 2012).

The image plane of left and right camera are located in the same plane, so the y coordinates of both images are the same ($Y_L = Y_R$) and the disparity is equal to the difference between the horizontal coordinates ($x_L - x_R$).

$$d = x_L - x_R = f \left(\frac{x_p + 1}{z_p} - \frac{x_p - 1}{z_p} \right) \quad (1)$$

1.3. Longan Leaf as Object Sample

Longan (also called *Dimocarpus Longan* or *Sapindaceae*) is a fruit plant from Southeast Asia. Longan plant has umbrella-like canopy shape and lush compound leaves with opposite arrangement along the stem. A stem has 3-6 pairs of leaflets. Upper leaf surface is glossy dark green in color. Leaf edge is flat with tapering tip, tapered base and pinnate leaf venation. The leaves grow on the limb with 6-9 leaves. The leaf ranges from 4-9 cm in length and 2-4 cm in width. **Figure 2** shows several types of Longan.

1.4. Texture Analysis Using Gray-Level Co-Occurrence Matrix (GLCM)

Gray-Level Co-occurrence Matrix (GLCM) is one of the well-known texture analysis methods to estimate the image properties related to second-order statistics (Lu *et al.*, 2012). The matrix is designed to measure the spatial relationship between pixels. This method is based on the belief that the information of texture is resulted from some relationships. Each entry (i,j) in GLCM is in accordance with the number of occurrences of a pair of gray levels i and j , which are separated by distance d as a distance in the original image.

To estimate the similarity between different gray-level co-occurrence matrices, some researchers used 22 features in his study and others also used a number of different features. In this study, 22 features were used as it is believed that the 22 features can distinguish objects well (Babaghorbani *et al.*, 2010; Ehsanirad, 2010; Ershad, 2011). These features were as follows:

- Angular Second Moment (Energy), indicating the size of the image homogeneity properties:

$$ASM = \sum_i \sum_j \{p(i,j)\}^2$$

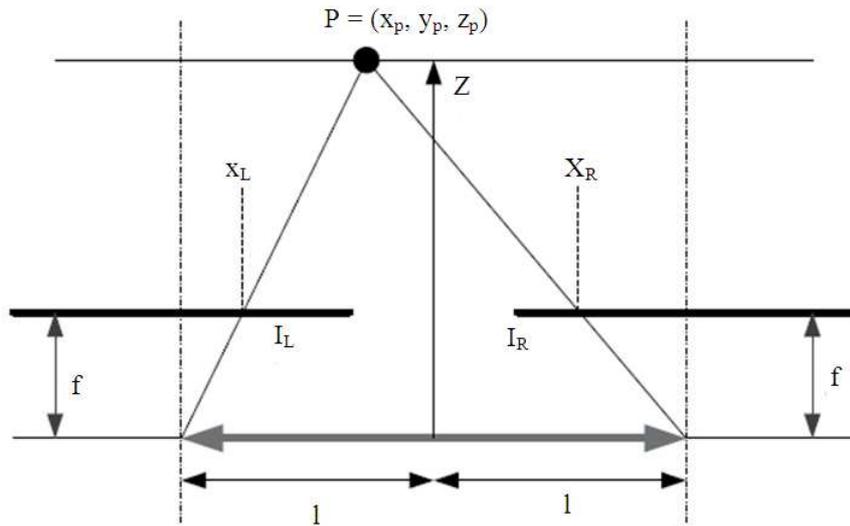


Fig. 1. A simple stereo system (Wang and Ju, 2009)

Aroma Durian	Diamon	Itoh	Kris-talin	Pim-pong
Ito super	Puanghai	Beekyu	Satu Jari	

Fig. 2. The variety of Longan Source: Telaga Nursery Prambanan, Pemukit baru, Tloga RT12 RW 04, Prambanan, Klaten

where, $p(i,j)$ states the values in row i and column j in the co-occurrence matrix:

$$COR1 = \frac{\sum_i \sum_j (ij) \cdot p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$$

- Contrast, indicating the size of image matrix element spread (moment of inertia):

$$CON = \sum_k k^2 \left| \sum_i \sum_{j=|i-k|} p(i,j) \right|$$

- Correlation 1, indicating the linear dependence of the size of the gray level, so providing guidance in a linear structure image:

where, σ_x and σ_y are standard deviation values of consecutively column and row elements in the matrix of $p(i, j)$:

- Correlation 2:

$$COR2 = \frac{\sum_i \sum_j p(i,j)(i - \mu_x)(j - \mu_y)}{\sigma_x \sigma_y}$$

- Autocorrelation:

$$AUC = \sum_i \sum_j (ij) \cdot p(i, j)$$

$$C_m = \max_{i,j} p(i, j)$$

- Variance, indicating variation of the co-occurrence matrix elements:

$$VAR = \sum_i \sum_j (i - \mu_x)(j - \mu_y) p(i, j)$$

where, μ_x dan μ_y are the average values of consecutively row and column elements in the matrix of $p(i, j)$:

- Inverse Different Moment (Homogeneity), indicating that the homogeneity of image at the same level is gray. The homogeneity of image IDM will have a great value:

$$IDM1 = \sum_i \sum_j \frac{1}{1 + |i - j|^2} p(i, j)$$

- Inverse Different Moment (Homogeneity) 2:

$$IDM2 = \sum_i \sum_j \frac{1}{1 + |i - j|} p(i, j)$$

- Different Inverse Normalized:

$$IDN = \sum_i \sum_j \frac{1}{|i - j|} p(i, j)$$

- Inverse Different Moment Normalized:

$$IDMN = \sum_i \sum_j \frac{1}{1 + (i - j)^2} p(i, j)$$

- Entropy, indicating the size of the form less shape. ENT with a great value is for gray level images with uneven transition, while that with a little value is for irregular image structure:

$$Ent2 = \sum_i \sum_j p(i, j) \cdot \log_2 p(i, j)$$

- Cluster Shade:

$$Cshad = \sum_i \sum_j p(i, j) \cdot (i - \mu_x + j - \mu_x)^3$$

- Cluster Prominence:

$$Cprom = \sum_i \sum_j p(i, j) \cdot (i - \mu_x + j - \mu_x)^4$$

- Maximum Probability:

- Sum Average (Mean):

$$AVER = \sum_{k=2}^{2G} k \sum_{i,j} p(i, j)$$

- Sum Entropy:

$$SE = \sum_{k=2}^{2G} \sum_{\substack{i,j \\ i+j=k}} p(i, j) \log p(i, j)$$

- Sum Variance:

$$SV = \sum_{i=1}^{2G} (1 - SE)^2 p(i, j)$$

- Difference Variance (Contrast):

$$DIVAR = \sum_{k=0}^{G-1} \sum_{\substack{i,j \\ |i-j|=k}} i^2 \log p(i, j)$$

- Difference Entropy:

$$DENT = \sum_{k=0}^{G-1} \sum_{\substack{i,j \\ |i-j|=k}} p(i, j) \log p(i, j)$$

- Dissimilarity:

$$Disim = \sum_i \sum_j |i - j| p(i, j)$$

- Information measured of correlation1

This information is generated from the correlation coefficient of normal distribution:

$$InfoCor1 = \frac{HXY - HXY1}{\max\{HX, HY\}}$$

Where:

$$HX = -\sum_i p(i) \log_2(p(i))$$

$$HY = -\sum_j p(j) \log_2(p(j))$$

$$HXY = -\sum_i \sum_j p(i, j) \log_2(p(i, j))$$

$$HXY1 = -\sum_i \sum_j p(i, j) \log_2(p(i)p(j))$$

$$HXY2 = -\sum_i \sum_j p(i)p(j) \log_2(p(i)p(j))$$

- Information measured of correlation 2:

$$\text{InfoCor2} = 1 - e^{-2 - (\text{HXY2} - \text{HXY})^2}$$

Information correlation coefficient is the probability density function of the joint distribution $p(x, y)$ of two variables x and y .

2. MATERIALS AND METHODS

In the recognition of Longan plant’s leaves, the Fujifilm 3D camera stereo was used as a tool to capture the leaf objects. Once the images were captured, STHmaker software was used to convert the file formats from .MPO to .JPG. The scheme of this research is shown in **Fig. 3**.

2.1. Input of Stereo Images

The amount of leaf images used was 600 pairs of left and right leaf images for the training data and 150 ones for the testing for each variety of Longan, so the total number for 9 varieties was 5400 pairs for the training data and 1350 pairs for the testing.

2.2. Segmentation

Leaf images were previously segmented before the disparity value of a pair of leaf images was calculated. The objective of the segmentation was to separate the objects from the background.

2.3. Stereo Correspondence and Stereo Map Calculation equations

In this step, a pair of left and right images was matched with each other. In the experiment, the selection of maximum disparity value (so-called dismax) and window value that was able to give better disparity outcomes was made. The disparity (comparison of two images) of the stereo images was obtained from stereo vision. However, this method only tells the position of the object to another object without any distance between positions.

SAD algorithm was one of the measures of inequality in the matching of left and right stereo images with a square window. It calculated difference in intensity for each central pixel (i, j) in the window $W(x, y)$ as follows:

$$\text{SAD}(x, y, d) = \sum_{(i, j) \in W(x, y)} |I_L(i, j) - I_R(i - d, j)|$$

where, I_L and I_R were functions of the pixel intensity of left and right images respectively. $W(x, y)$ was a square window centered at (x, y) pixel and d was the maximum disparity.

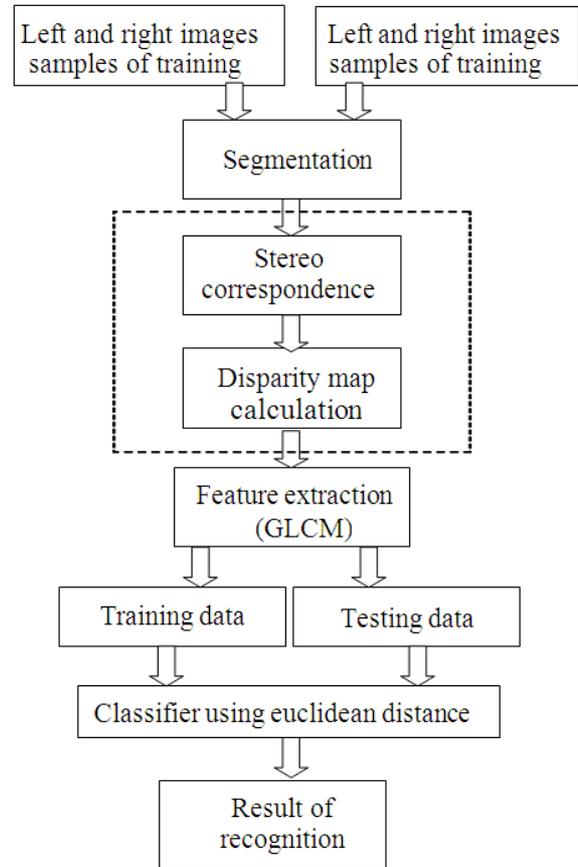


Fig. 3. Research scheme

2.4. Feature Extraction using GLCM

Once the difference value was obtained from each pair of the leaf images, 22 features were extracted by using GLCM features (second order statistics).

2.5. Euclidean Distance Similarity

At each pattern matching process, a measure that can provide information about the similar characteristics of compared images was required. For those with vector-shape characteristics (such as Fourier spectrum, edge and texture), Euclidean distance was commonly used to measure the similarity with the following formula:

$$d(x, y) = \|x - y\| = [(x_1 - y_1)^2 + \dots + (x_n - y_n)^2]^{1/2}$$

where, y was a vector containing the characteristic values of input property and x was a vector containing the characteristic values of the model owned.

3. RESULTS

The implementation of the research scheme was done using Matlab 7. Results of the implementation are shown in **Fig. 4**.

First, each pair of the left and right leaf images was taken from leaf images in image database folder.

Second, each leaf image was segmented, so that the images containing original objects (colorful) with white background were produced. Before segmented, each leaf image was resized into the ratio of 500×500, adjustments were made, conversions were done from RGB format into gray scale format and the threshold was determined to be able to separate objects from the background.

Third, both disparity map and stereo correspondence were calculated by the SAD method. The calculation of SAD (x, y, d) disparity was repeated within the framework of x coordinate in the drawing lines, which were defined by zero and the possible maximum disparity (dismax) of 3D scene searched. The minimum value of difference in frame indicates the best matching pixel and the minimum position defines difference from the actual pixel. The quality of 3D disparity maps depends on the size of the square window, because the larger size of such square window in accordance with the greater probability of true difference in pixel is calculated from the match point, though the calculation will be slower (Kamencay *et al.*, 2012). In this experiment, the dismax value of 7 and the square window of 3 were selected.

Fourth, disparity results were refined by using a polynomial transformation to improve the image quality.

Finally, the matching was done using the Euclidean distance. By the Euclidean distance, it takes only a single process, i.e., to measure the features of distance from the features of the training data and to compare each distance to get the minimum distance.

The implementation of the matching of Longan plant varieties was done by using some variations in the number of varieties and in three different distances. Results of the matching can be seen in **Fig. 5**.

Based on **Fig. 5**, it can be seen that the highest accuracy was obtained in the recognition of three plant varieties with 50 cm camera distance, i.e., 83.3%. Meanwhile, **Table 1** shows the classification errors in the recognition of three plant varieties with 50 cm camera distance.

Variety 1 was recognized as variety 1 with 60% and recognized as variety 3 with 40%; variety 2 was recognized with 100%; and variety 3 was

appropriately recognized with 90% and recognized as variety 1 with 10%.

Table 1. The result of recognition among three plant varieties with 50 cm camera distance

Varietas	1	2	3
1	60	0	40
2	0	100	0
3	10	0	90

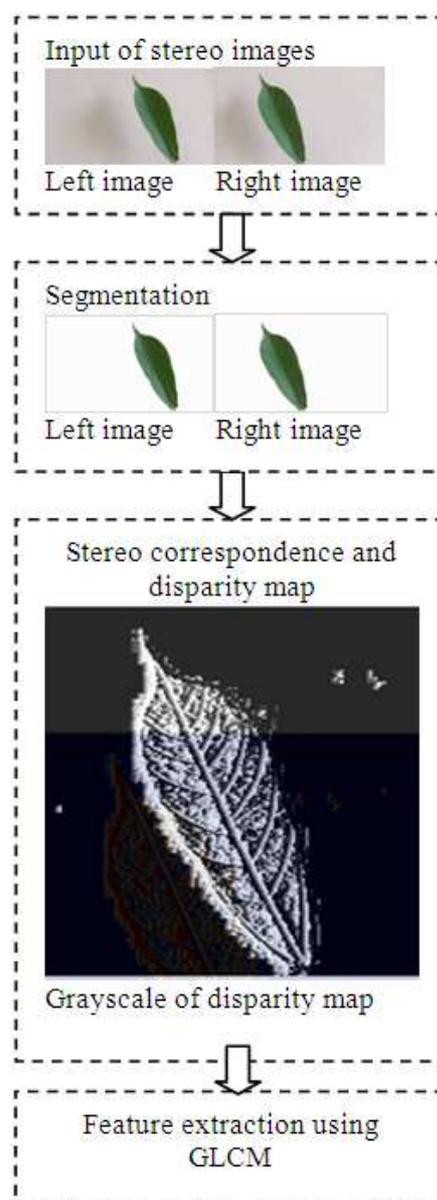


Fig. 4. Result of research schema

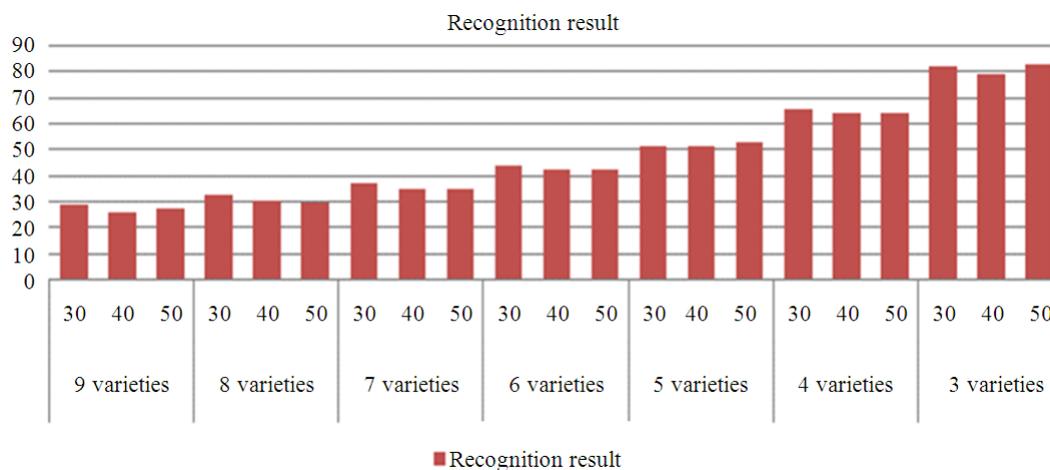


Fig. 5. The result of similarity among nine plant varieties in three different camera distances

4. DISCUSSION

Based on **Table 1**, the result of recognition among three plant varieties using 3D leaves images is 83,3%. It have low accuracy compared with plants recognition using 2D leaves images.

In recognizing 3 leaves types using two different shape modeling techniques, i.e., Moments-Invariant (MI) model and Centroid-Radii (CR) model, the accuracy is 90-100% using Artificial Neural Network (Chaki and Parekh, 2011). Moreover, in recognition of 3 different leaves images groups with varying size and lighting using combined feature extraction by Transform Gabor, local Phase Quantization (LPQ) and Principle Component Analysis (PCA), the accuracy is 84,89% with Support Vector Machine as the classifier (Venkatesh and Raghavendra, 2011).

Factors causing high accuracy in leaves recognition in the previous study compared with current study are, first, plant types recognized tend to have different characteristics. Pornpanomchai *et al.* (2011a) and Kadir *et al.* (2011) identify 32 herb types with different shape characteristics. Second, the entire leaves objects in input images had similar positioning, which was frontal position. Third, input images used were 2D images. Meanwhile in this study plants recognition was done between varieties with high similarity.

In this research we use disparity map features of images. Plants recognition based on stereo images should have higher accuracy. This was because 3D stereo images will give more detailed information compared with 2D images. Therefore, plants recognition based on

3D stereo images should be developed using more accurate models. In future work, we will develop a preprocessing technique to identify leaves images using depth map from stereo images.

5. CONCLUSION

This study proposed plant recognition based on stereo leaf images using 22 features of Gray Level Co-occurrence Matrix. The implementation of matching was done with some variations in number of plant varieties in three different camera distances, i.e., 30, 40 and 50 cm. By using the similarity in Euclidean distance, some resultant accuracy of the matching was produced. The highest accuracy of the matching in the recognition of plant variety was obtained at 50 cm camera distance and the recognition of three plant varieties was 83.3%. Therefore, the new scheme of plant recognition based on the stereo leaf images provided better but not optimum results, so the system is necessary to develop in the future by taking the depth of image into account.

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