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The use of machine vision technique to classify cultivated rice seed variety and weedy rice seed variants for the seed industry

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Abstract

Seed purity is a crucial seed quality parameter in the Malaysian rice seed standard. The use of high quality cultivated rice seed, free of any foreign seeds, is the prerequisite to sustaining high yield in rice production. The presence of foreign seeds such as weedy rice in the cultivated rice seeds used by the farmers can adversely affect growth and yield as it competes for space and nutrients with the cultivated rice varieties in the field. Being the most dominant and competitive element compared to the cultivated rice seeds, the Malaysian seed standard prescribed that the maximum allowable of weed seeds in a 20-kilogram certified rice seed bag produced by local rice seed processors is 10 weed seeds per kilogram. The current cleaning processes that rely mostly on the difference in physical traits do not guarantee effective separation of weedy rice seeds from the lots. Seed bags found to contain more than 10 weed seeds upon inspection by the enforcing agency will not be approved for distribution to farmers. The paper describes a study carried out to explore the use of machine vision approach to separate weedy rice seed from cultivated rice seeds as a potential cleaning technique for the rice seed industry. The mean classification accuracies levels of the extracted morphological feature model were achieved at 95.8% and 96.0% for training and testing data sets respectively.

Introduction

The use of high quality seed, free of any foreign seeds, is the prerequisite to a sustainable rice production. Foreign seed such as weedy rice is the most dominant and competitive weed in the field affecting growth and yield as it competes for space and nutrients with the cultivated rice varieties. Seed contaminated with weedy rice seeds is one of the three major sources of weedy rice infestation in the field (Labrada, 2007). Under high weedy rice infestation, the yield loss can be between 15 to 22%, while under heavy infestation, lodging of weedy rice plants can even cause total yield loss (Azmi and Abdullah, 1998). This is a significant yield and income loss to the nation and farmers if seed purity is compromised. Varietal purity in the seed is also important as it can affect production practices (Seshu and Dadlani, 1989) which may inadvertently lead to higher production costs. Such a demand on seed purity especially in the staple food crop production has put pressure on the commercial seed producers and processors to produce seeds meeting the industry standard.

In a typical Malaysian rice seed processing plant, the harvested rice seeds are first subjected to pre-cleaning followed by various cleaning processes before and after drying. The cleaning processes that rely mostly on the difference in material densities will not guarantee effective separation of weedy rice seeds from the lots. As a consequent, most of the commercial seed processors installed inclined indented rotating cylinder as a final process to mechanically separate weedy rice from the cultivated rice seeds by the difference in their lengths before bagging. However, its effectiveness is influenced by the presence of weedy rice seed variants having similar length as the cultivated rice seeds.

Machine vision system is one of the emerging technique which can be used as an alternative method to enhance the seed separation efficiency beyond the current techniques. Typically, seed inspection and separation using machine vision technique are conducted in seed grading, variety classification and quality monitoring such as identification of foreign matter, insect infestation and microbial infection, and discoloured grains (Vithu and Moses, 2016). Apart of these, many studies using machine vision

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system to classify seed varieties has been reported by Dubosclard *et al*. (2015); Rad *et al*. (2012); Zapotoczny *et al*. (2008); Liu *et al*. (2005) and Majumdar and Jayas (2000).

The common extracted features from the seed images are morphology (Rad, Tab, and Mollazade, 2012) colour (Golpour, Parian, and Chayjan, 2014), texture (Zapotoczny, 2012) and the combination of more than one feature (Anami *et al*., 2015; Hernandez and Gil, 2011).

The use of such technique requires various classification analyses using a computer learning algorithm to classify different seeds and grains. Among them were discriminant analysis, principal component analysis, naïve Bayes and neural network as used by different researchers (Zapotoczny *et al*., 2008; Granitto *et al*., 2002 and Majumdar and Jayas, 2000). This research aimed to adopt machine vision technique to separate cultivated rice seed of MR 263 and weedy rice seed variants using one of the classification analyses. For this study, discriminant analysis is used as it is more widely used.

Material and Method

Collection of seed samples

Five different types of weedy rice seeds variants (close panicle; partly short awned-open panicle; close panicle; partly short awned-close panicle; and partly long awned-close panicle) were collected from several commercial farms in Kedah. One hundred and twenty kernels from each variant were selected for weedy rice seeds samples. The local cultivated rice seeds MR 263 was collected from a commercial rice seed bag from a local supplier. The seeds from the bag were separated to ensure only MR 263 seed kernels were selected for the sample. The total number of cultivated rice seed MR 263 used in this study was 600 kernels and the other 600 kernels was the weedy rice seeds variants kernels with the overall number of seed kernels used was 1,200. From each group, 353 (60%) seeds and 247 (40%) seeds as were used as training and testing data set respectively.

Machine vision system

A charge-coupled device (CCD) Basler colour camera model acA1600-20gc was used for image acquisition. The camera was fitted with 12 mm focal length lens. It was mounted on top of a black box (60.8 cm length x 30.55 cm breadth x 60.0 cm height) perpendicular to the seed plate position. In the black box, two light-emitting diode (LED) light bulbs of 6400 K colour temperature were placed on both sides of the seed plate for an even illumination. The field of view (FOV) of the camera were adjusted to cover two rows of seed holes which contained 8 seed holes in an image frame. The distance between camera lens and the seeds was 7.4 cm. A fluorescent green surface seed plate with the elliptical holes was used to place the seed kernels for image acquisition.

Image acquisition

The individual seed kernels were placed on the seed plate (8 kernels/image) and images were acquired and stored for image processing and analysis. A spatial calibration was carried out using an object of known dimension which was a Malaysian 50 cent coin. All images were acquired in Red, Green and Blue (RGB) colour model and stored in Portable Network Graphics (PNG) format with 2-megapixel resolutions (1628 x 1236 pixels). The acquired images were loaded in LabVIEW for image processing and analysis.

Image processing and morphological characteristics extraction

The software applications used in this study was LabVIEW 2012 (National Instruments Corporation, 2000) development environment for image processing and morphological features extraction. Flow diagram of steps in image processing, extraction of morphological features and seed classification procedure of training and testing the classification model was accomplished according to Figure 1.

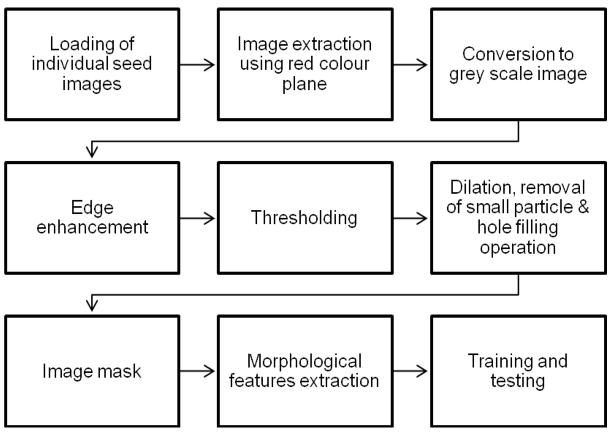

Figure 1. Flow diagram of the methodology

First, the image was loaded in LabVIEW and was defined to be extracted by red colour plane. Then the image was converted to grey scale image for further processing followed by edge enhancement using Laplacian filters. Then, the image was thresholded to separate the seed kernels image from the background image. After thresholding, dilation operation was carried out to close the contours of every seed grains images (Hernandez and Gil, 2011).

Next, small particles were removed to get a clean image by eliminating noisy particles and unwanted particles formed on the background image. Then, hole filling operation was employed to fill any holes found in seed kernel images with pixel value 1. The final operation was carried out by copying the image source that corresponded to a non-zero pixel value in the mask image to display the processed image. The sample images of individual kernel before and after image processing can be obtained in Figure 2.

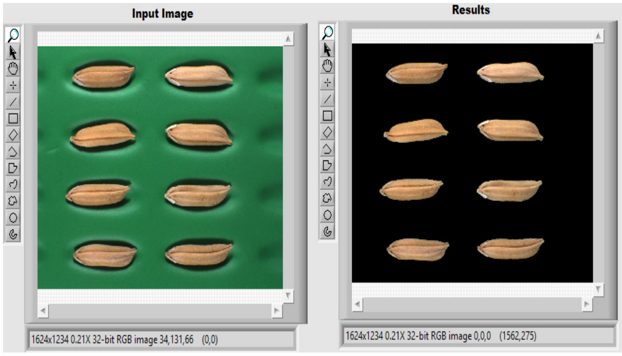

Figure 2. Sample of individual seed image of before and after image processing

The morphological features (Table 1) of individual seed kernels were carried out to extract the following features (Cheng *et al*., 2005). All the obtained values were multiplied by the calibration factor (mm/pixel) to convert pixels unit to millimeter (mm).

Table 1. Morphological features extraction

Features	Descriptions
Area (mm^2)	The algorithm calculated the number of pixels of the boundary and pixels inside of the seed.
Length (mm)	The length of the rectangle bounding the seed.
Width (mm)	The width of the rectangle bounding the seed.
Major axis length (mm)	The distance between the end points of the longest line that could be drawn through the seed. The major axis endpoints were obtained by computing the pixel distance between every combination of border pixels in the seed boundary and finding the pair with the maximum length.
Minor axis length (mm)	The distance between end points of the longest line that could be drawn through the seed while maintaining perpendicularity with the major axis.
Thinness ratio	The measurement of roundness of the seed. Thinness ratio = $(\text{Perimeter})^2 / (4\pi \times \text{Area})$
Aspect ratio	The ratio of major axis length over minor axis length.
Rectangular aspect ratio	The ratio of length over width.
Equivalent diameter (mm)	The diameter of a circle with the same area as the rice seed region. Equivalent Diameter = square root ($4 \times$ Area / π)
Convex area (mm^2)	The number of pixels in the smallest convex polygon that can contain the rice seed region, and multiplied by the calibration factor (mm^2/pixel).
Solidity	The proportion of the pixels in the seed region that are also in the convex hull. Solidity = Area / Convex area
Extend	The proportion of the pixels in the bounding box that are also in the seed region. Extend = Area / Area of the bounding box

Statistical analysis

The morphological features data analysis was performed using Statistical Package for the Social Sciences (SPSS) version 20.0 software. A stepwise discriminant function analysis (DFA) was carried out in SPSS software to develop a discriminant formula to classify cultivated rice and weedy rice seeds variants. Wilks' lambda method was employed for features selection in stepwise DFA. The analysis was conducted using cross-validation and hold out methods. In the hold out methods, a total of 706 seed kernels (353 seed kernels per seed group) were used as training data set and 494 seed kernels (247 seed kernels per seed group) were used for testing data set using an independent data set. Both data sets were randomly selected using Bernoulli distribution. In cross-validation method, 706 seed kernels images that were used as the training data set in the hold out method were also used for classification.

Results and Discussion

Using stepwise DFA, only 7 out of 12 extracted morphological features were selected after seven steps in the analysis. Table 2 shows the standardized and unstandardized coefficients, structure matrix, group centroid and sectioning points for the discriminant function. The standardized coefficients values provide an index of the importance of each feature. The positive and negative signs indicate the direction of the relationship. The structure matrix values showed the correlations of each morphological feature with the discriminate function of Equation 1.

The unstandardized coefficients obtained from Table 2 were used to develop the discriminant function of Equation 1 as follow:

$$F = 10.954 \text{ (Minimum Axis Length)} + 1.867 \text{ (Rectangular Aspect Ratio)} + 1.227 \text{ (Aspect Ratio)} + 0.816 \text{ (Length)} + 0.545 \text{ (Area)} - 1.214 \text{ (Convex Area)} - 302.810 \text{ (Extend)} - 27.625 \quad (1)$$

Table 2. Discriminant coefficients for discriminant function of Equation 1

Morphological features	Standardized coefficients	Structure matrix	Unstandardized coefficients	Group centroids		
				Weedy rice	MR 263	Cut-off point
Area	0.998	0.056	0.545	-1.644	1.821	0.089
Aspect Ratio	1.509	-0.277	1.227			
Convex Area	-3.348	-0.063	-1.214			
Extend	-0.403	0.176	-302.810			
Length	1.227	0.040	0.816			
Minimum Axis Length	2.078	0.486	10.954			
Rectangular Aspect Ratio	1.049	0.155	1.867			
Constant	-	-	-27.625			

Table 3. Classification accuracies level of the morphology model for training and testing data sets

Data Set			Group	Predicted Group Membership		Mean	Total
				MR 263	Weedy rice		
Training	Original	Count	MR 263	334.0	1.0	-	371
			Weedy rice	30.0	341.0		335
		% Accuracy	MR 263	99.7	0.3	95.8	100
			Weedy rice	8.1	91.9		100
	Cross Validation	Count	MR 263	334.0	1.0	-	371
			Weedy rice	31.0	340.0		335
		% Accuracy	MR 263	99.7	0.0	95.7	100
			Weedy rice	8.4	91.6		100
Testing	Original	Count	MR 263	262.0	3.0	-	265
			Weedy rice	16.0	213.0		229
		% Accuracy	MR 263	98.9	1.1	96.0	100
			Weedy rice	7.0	93.0		100

In order to determine an unidentified seed belongs to which population group, the value of each morphological features as in the discriminant function (Equation 1) is multiplied with the respective unstandardized coefficient and added to the constant value. If the computed value is greater than the cut-off point (0.089), the unidentified seed is considered as cultivated rice MR 263 and if the value is less than the cut-off point, the unidentified seed is considered as weedy rice seed.

The classification accuracy levels of the discriminant function (Equation 1) describing weedy rice and cultivated rice seed MR 263 is presented in Table 3. When the training data set mean was used, the classification accuracy was 95.8%. Upon cross-validation, the mean accuracy of the function was 95.7%; which is very close to the original accuracy level of the training data set; this validated that the training data set was reliable. However, when testing data set was used in the discriminant function, the mean classification accuracy was 96.0%.

Therefore, the classification results obtained from the developed discriminant function using morphological model showed very high classification accuracy levels for both training and testing data set. The range of accuracies are comparable with the works of Hernandez and Gil (2011) and Paliwal *et al*. (2003) and Majumdar and Jayas (2000), whose accuracies levels were found between 96.0% to 99.0%. The findings underscore the viability of the machine vision system as a potential process to separate weedy rice from cultivated rice seeds that can be benefited by rice seed processing industry to enhance the production of high quality seed.

Conclusion

Discriminant analysis is therefore a viable classification technique to classify cultivated rice seed MR 263 and weedy rice seed variants. This is reflected in the high level of classification accuracy (95.8% and 96.0% for training and testing data sets) comparable with accuracy levels obtained in other related studies for different types of cereal grains. Separation of weedy rice seed from cultivated rice seed can be achieved using machine vision approach to enhance separation efficiencies for the benefit of the seed industry.

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