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Paddy/Rice Singulation for Determination of Husking Efficiency and Damage Using Machine Vision

M. Shaker, S. Minaei, M. H. Khoshtaghaza, A. Banakar, A. Jafari

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Abstract—In this study a system of machine vision and singulation was developed to separate paddy from rice and determine paddy husking and rice breakage percentages. The machine vision system consists of three main components including an imaging chamber, a digital camera, a computer equipped with image processing software. The singulation device consists of a kernel holding surface, a motor with vacuum fan, and a dimmer. For separation of paddy from rice (in the image), it was necessary to set a threshold. Therefore, some images of paddy and rice were sampled and the RGB values of the images were extracted using MATLAB software. Then mean and standard deviation of the data were determined. An Image processing algorithm was developed using MATLAB to determine paddy/rice separation and rice breakage and paddy husking percentages, using blue to red ratio. Tests showed that, a threshold of 0.75 is suitable for separating paddy from rice kernels. Results from the evaluation of the image processing algorithm showed that the accuracies obtained with the algorithm were 98.36% and 91.81% for paddy husking and rice breakage percentage, respectively. Analysis also showed that a suction of 45 mmHg to 50 mmHg yielding 81.3% separation efficiency is appropriate for operation of the kernel singulation system.

***Keywords*—**Computer vision, rice kernel, husking, breakage.

I. Introduction

EVER increasing world population and demand for food supply necessitates improving agricultural production and reducing processing losses. In this regard, reducing rice milling losses is important. In the milling process for turning paddy into white rice, paddy hulling operation is of utmost importance, making it essential to undertake research efforts to optimize these processes, as discussed below.

In the face of increasing global demand for food production, limited cultivated area and drought crises, it is imperative to reduce production losses. Milling is one stage of rice production in which loss reduction is important. This stage includes four sub-stages of cleaning, husking, whitening and grading of rice. In each of these sub-stages rice can incur damages, which decreases product quality and economic value. Quality of rice is expressed using indicators such as: head rice, unripe, cracked, broken, chalky, over-dried and damaged. Given that the price of broken rice is about half that of head rice, studying these indicators is important from an economic point of view [1].

Due to the nature of paddy husking in the milling process, a portion of the qualitative losses appears at this stage since it is a high-intensity mechanical process. Manual methods are traditionally used for determining quality indicators of rice losses during the husking operation. These methods are time-consuming and labor-intensive, while image processing can be a quick, effective way to control and improve the performance of husking devices.

A large body of research has been conducted to identify qualitative factors and dimensions of brown and white rice grains using digital image processing. Most studies have focused on measuring rice breakage, head-rice yield and rice milling as well as controlling the degree of whiteness by using a computer equipped with appropriate software for image processing. A brief review of such studies is given below.

To analyze the shapes of brown and polished rice kernels, a series of measurements by image processing on *Japonica, Indica* and *Javanica* types composed of four rice varieties with three polishing methods were carried out. Parameters including area, perimeter, maximum length, maximum width, compactness and elongation were measured. The maximum length, maximum width and elongation of a rice grain were different from the traditional dimensions such as length and width. Further, separating rice varieties using shape differences was examined. Analysis of brown and polished rice kernels showed that separating rice varieties was possible at a probability level of 95.4% using a single dimension or shape factor or a combination thereof [2].

A digital image analysis method was developed to quickly and accurately measure the Degree of Milling (DOM) for rice. The digital image processing method was statistically compared to a chemical analysis method for evaluating DOM. The latter consisted of measuring Surface Lipids Concentration (SLC) of milled rice. The Surface Lipid Area Percentage (SLAP) obtained by the image processing method and the SLC obtained by chemical analysis had a high coefficient of determination using a quadratic model and a logarithmic model. The quadratic and logarithmic models were validated using a test data set, producing high coefficients of determination [3].

M. Shaker is Graduated Ph.D. with the Biosystems Eng. Dept., Tarbiat Modares University, Tehran, Iran (phone: 09171113691; e-mail: m.shaker1348@gmail.com).

S. Minaei and M. H. Khoshtaghaza are Associate Professors with the Biosystems Eng. Dept., Tarbiat Modares University, Tehran, Iran (e-mails: minaee@modares.ac.ir and khoshtag@modares.ac.ir).

A. Banakar is Assistant Professor with the Biosystems Eng. Dept., Tarbiat Modares University, Tehran, Iran (e-mail: ah_banakar@modares.ac.ir).

A. Jafari is Assistant Professor with the Biosystems Eng. Dept., Shiraz University, Shiraz, Iran (e-mail: ajafari@shirazu.ac.ir).

Milled rice kernels from a laboratory mill and a commercial-scale mill were evaluated for HRY using a shaker table and a machine vision system called GrainCheck. Comparisons were made for both medium and long grain rice varieties. For each variety, samples having different amounts of broken kernels were analyzed to determine the performance of both instruments over a range of HRYs. Head rice was also measured based on FGIS[1] for commercially milled samples to compare the shaker table and the GrainCheck with an official measurement. HRY values were significantly different between the two instruments for all samples; the mean HRY variation was, however, equal for both instruments [4].

The performance of an automatic inspection system for rice quality classification was examined. The system sorted rice into sound, cracked, chalky, immature, dried, broken, damaged, and off–type kernels. A rice quality inspection software was developed to provide sorting parameters and to improve the accuracy of sorting and machine operation. Test results showed that the automated inspection system could correctly categorize over 90% of rice kernels, as compared to human inspection. Results for sound, chalky, and cracked kernels indicated high accuracy (around 95%, 92%, and 87%, respectively) for each category. The average processing speed for online rice quality inspection was over 1200 kernels/min [5].

Digital image processing was applied to determine the geometrical features as well as color of rapeseed surface, and to detect some impurities that are difficult to detect in the cleaning process [6]. Several shape features of corn plants and common weed species in the location were extracted by means of morphological operations. Effective features in the classification of corn and weeds were analyzed using stepwise discriminant analysis. Results showed that this technique was able to distinguish corn plants with an accuracy of 100%, while at most 4% of the weeds were incorrectly classified as corn [7].

Moisture content of paddy was predicted using machine vision and artificial neural networks. The grains were dried as thin layer with air temperatures of 30, 40, 50, 60, 70, and 80°C and air velocities of 0.54, 1.18, 1.56, 2.48 and 3.27 ms-1. Kinetics of $L^*a^*b^*$ were measured. The air temperature, air velocity, and $L^*a^*b^*$ values were used as ANN inputs. The results showed that with increase in drying time, L* decreased, but a^* and b^* increased. The effect of air temperature and velocity on the $L^*a^*b^*$ values were significant ($P< 0.01$) and not significant ($P> 0.05$), respectively [8].

Image processing techniques for moisture content determination of rough rice was used and evaluated. This measurement method uses drying time as a variable under constant hot air temperature and humidity. An image acquisition system is used to set multiple thresholds for the color histograms of the images (rough rice with stalks is placed in the test carrier). Based on the distribution of the colors, the stalk images are separated from the rough rice images, and edge enhancement and shape detection are applied to more accurately acquire specific detected areas from the image. Finally, based on the specific colors of the stalks, the moisture content of rough rice can be determined [9].

A handheld device was developed for easily capturing planthopper images on rice stems and an automatic method for counting rice planthoppers based on image processing. The handheld device consists of a digital camera with WiFi, a smartphone and an extendable pole. They used this method to detect and count whiteback planthoppers on rice plant images and achieve an 85.2% detection rate (with a 9.6% false detection rate). The method is introduced as an easy, rapid, and accurate for the assessment of the population density of rice planthoppers in paddy fields [10].

In order to determine the location and type of rice chalkiness accurately, image processing techniques were adopted to process acquired rice kernel images. Connected rice kernels were separated from each other using a convex point matching method. Chalkiness was extracted based on the differences in grayscale levels between chalky and normal regions in the rice kernel. Chalky rice kernels were classified using support vector machine (SVM). The results showed that 2–5 connected rice kernels could be separated accurately using this method and chalky areas could be extracted. The classification accuracy for indica rice and japonica rice reached 98.5% and 97.6%, respectively, by using SVM [11].

Colour parameters of sweet cherries were predicted by combining image processing and artificial neural network (ANN) techniques. The color measuring technique consisted of a CCD camera for image acquisition, MATLAB software for image analysis, and ANN for modeling. After designing, training, and generalizing several ANNs using Levenberg-Marquardt algorithm, a network with 7-14-11-3 architecture showed the best correlation (R2= 0.9999) for L^*, a^* and b^* values from Chroma meter and the machine vision system. L^* and b^* parameters decreased during ripening of cherries and a^* parameter increased at first and then decreased [12].

Review of previous studies reveals that using digital image processing technology is an efficient, accurate method for detecting and measuring the qualitative and appearance factors of rice kernels and other agricultural products. Most studies, however, have used image processing to measure the characteristics of milled rice (the output of millers), with dehusker and its output being neglected. The aim of the present study was to apply a machine vision system to separate paddy from brown rice and determine the percentages of paddy husking and rice breakage.

II. Materials and Methods

The machine vision system has three main components including an imaging chamber, a digital camera, and a computer equipped with image processing software. For the purpose of this research, a 30 cm × 30 cm × 30 cm chamber was made to capture images as described below (Figs. 1 and 2).

[1]. Federal Grain Inspection Service.

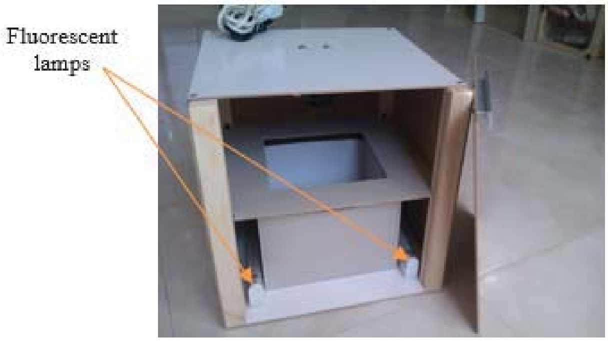


Fig. 1 Imaging chamber and the position of fluorescent lighting

Fig. 2 Position of the webcam in the imaging chamber

An A4TECH 16 Megapixel webcam was used to take images, which was mounted on the top part of the chamber on a metal frame. A camera resolution of 640 pixels × 480 pixels was set, with which Paddy was recognizable from rice kernels. The camera was connected via the USB port to a PC, and images were taken using MATLAB software and the appropriate settings. A middle plate with a square cut out of the centre was placed in the mid-section of the chamber to prevent light reflection toward the camera. Two 25 cm white fluorescent lamps were used for lighting. Pilot tests showed that the best place to install them is at the bottom of the chamber.

For imaging paddy and rice kernels and to develop an image processing algorithm, it was necessary to design a mechanism for singulation (separating kernels from each other). This can help simplify the coded algorithm through direct extraction of kernel features. For this purpose, a 20 cm × 20 cm × 3 cm metal box was constructed. A matrix of 1mm holes spaced 15mm apart totaling 121 were drilled on one side of the box (kernel-holding surface). A 1400 watt motor equipped with suction fan embedded in the chamber was used to create suction in the metal box. The two boxes were connected using a flexible pipe. Rotational speed of the motor was adjusted using a 2000 watt dimmer to provide sufficient suction to hold the kernels against the kernel-holding surface (Fig. 3).

The combination of machine vision and singulation systems along with the electric board and related connections, were mounted on a chassis as shown in Figs. 3 and 4. A DC motor having an output torque of 10 kg.cm rotating at 10 rpm was employed for supplying the tilting movement of the Kernel Holding Box (KHB). To do this, an electric board was prepared to control the (on-off) operation of the motor using embedded microswitches. First the control moves the KHB to its upright position (signaled by a limit switch). Meanwhile, the suction device starts to operate and a solenoid opens the by-pass outlet valve simultaneously to allow the kernels (including paddy and brown rice) to pour onto the KHB. After a few seconds (adjustable), the solenoid stops and while the suction device is on, the metal box with the adhering kernels (held by suction) starts tilting. The remaining kernels fall down due to gravity. At the lowest position, by hitting the lower limit switch, KHB stops and imaging is performed. After a few seconds (adjustable time), the suction is interrupted allowing all the kernels to drop due to gravity.

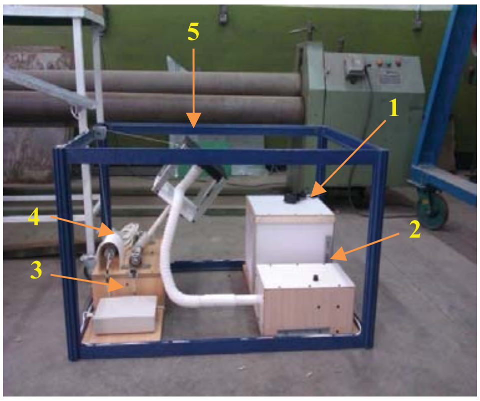


Fig. 3 Machine vision and singulation systems 1. Imaging chamber, 2. Suction system, 3. Electronic board, DC motor 5. Kernel holding surface

Fig. 4 Kernel holding surface and the related connections (Top view)

Using the above mentioned apparatus, kernel singulation is achieved as follows. First the chamber is positioned such that the Kernel Holding Surface (KHS) is horizontal. When the paddy/rice mixture is poured onto the box, the suction force retains the kernels on the holes against the KHS. By tilting the box from its horizontal position, the extraneous kernels not positioned on the holes fall due to gravity. As the holes are located at a distance from each other, kernels held against the KHS are completely separated from each other. It was observed that due to the high suction provided by the motor, in some cases two or more kernels would be held against one hole. This was addressed using the dimmer to adjust the rotational speed of the motor and thus its suction force. When the lighting and imaging operations were carried out, data were transmitted to the computer through a USB port, simultaneously. These data were stored in a file accessible by MATLAB software for processing.

The whole system was evaluated in three replications. A mixture of paddy, head, and broken rice kernels were poured onto the kernel holding surface using a trough. The kernels were then separated automatically using the suction and singulation system after which, the image processing algorithm was executed. The percentages of paddy husking and rice breakage were then calculated and displayed on the screen.

For coding the image processing algorithm, it was necessary to calculate a threshold (for separation of paddy from rice). For any variety of paddy (medium or long grain) only one sampling was required to perform the necessary calculations to determine the threshold value using MATLAB software. Subsequently rice breakage and paddy husking percentages are easily calculated and every time a sample image is captured.

For determining the threshold, a few images of paddy, brown rice, and green rice (unripe) were acquired. In order to reduce the image processing operations, a part of each image was sampled using MATLAB software (50 samples of 4×4 pixels for each). For instance, 800 pixels were sampled from paddy kernel images and processed to separate the RGB. Results were saved and mean as well as standard deviation were calculated. This helped in quantifying the paddy, brown and green rice samples and to determine their thresholds. B and R color ratios were calculated to be used for thresholding, if necessary.

The image processing algorithm for separation of paddy from rice and calculation of paddy husking and rice breakage percentages was developed and coded in two spaces in MATLAB software. First, the binary or B&W space was utilized to determine the number of broken rice grains, and then the color space was employed to separate paddy from brown and green rice samples by thresholding the colors.

III. Results and Discussion

An example of the results of separated RGB colors for paddy kernels is presented in Table I. The means and standard deviations of data are presented in Table II. They show that the B/R color ratio can be used as a threshold to separate paddy from brown and green rice kernels. This threshold, which is approximately 0.75 (Fig. 5), can be included in an algorithm for separation purposes. It should be noted that the values of colors in MATLAB were usually in the class of unit eight, where values range from zero to 255. However, in the class of double, data are between zero and one and their true value is kept unchanged while computing the color values. Therefore, all data were first converted to the class of double before being used.

TABLE I
Results of the RGB Separation for Paddy Kernels

Row	Red (R)	Green (G)	Blue (B)	Blue/Red (B/R)
1	0.694	0.584	0.4	0.576
2	0.659	0.549	0.365	0.553
3	0.706	0.592	0.357	0.505
4	0.737	0.623	0.388	0.526
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0
797	0.827	0.698	0.498	0.602
798	0.843	0.690	0.459	0.544
799	0.831	0.678	0.447	0.538
800	0.831	0.674	0.431	0.519
Mean	0.753	0.635	0.449	0.595
Standard deviation	0.065	0.074	0.086	0.092

TABLE II
Mean and Standard Deviation of Data by Color and Kernel Type

Crop Type	Mean ± Standard deviation (σ ± μ)			
	Red (R)	Green (G)	Blue (B)	Blue/Red (B/R)
Paddy	0.75±0.06	0.63±0.07	0.45±0.09	0.60±0.09
Brown rice	0.74±0.07	0.72±0.06	0.64±0.07	0.86±0.05
Green rice	0.55±0.08	0.60±0.08	0.50±0.09	0.90±0.09

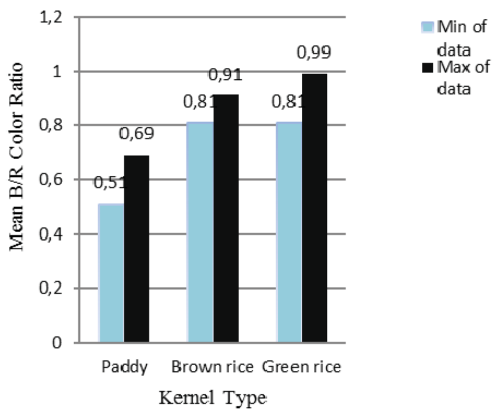


Fig. 5 Mean B/R color ratio by kernel type

A flow chart of the image processing algorithm for determining the percentages of paddy husking and rice breakage is presented in Figs. 6 and 7 explained below. Through this algorithm, first, the camera was detected and the necessary settings for resolution (640×480 pixels) and color image were produced. Then color image is loaded and is converted into binary. Head rice is separated from broken rice in the black and white (B&W) space using the kernel surface area (the number of white pixels). Thus, before coding the algorithm, it was necessary to calculate the area of a head-rice kernel, based on which the broken kernels were detected. For this purpose, 30 images of head-rice kernels were prepared, and their mean surface area was calculated. Kernels with areas smaller than three quarters of this mean value were counted as broken. For the medium grain rice (Champa variety), the mean head kernel area was about 140 pixels. Therefore, kernels smaller than 105 pixels were considered as broken.

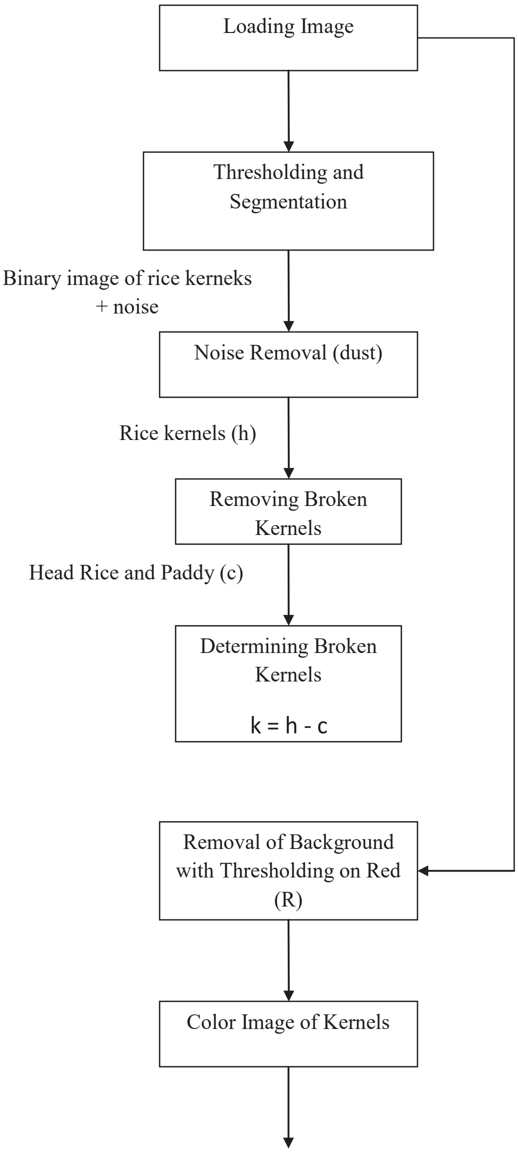


Fig. 6 Flow chart of the Image processing algorithm

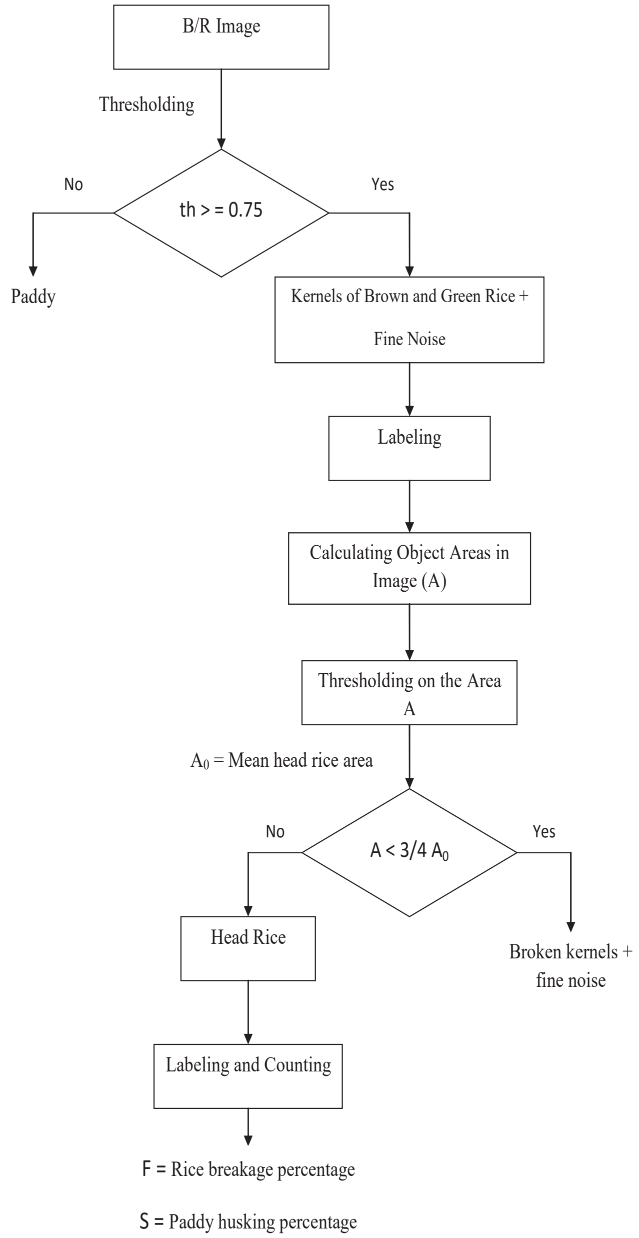


Fig. 7 Flow chart continue of the Image processing algorithm

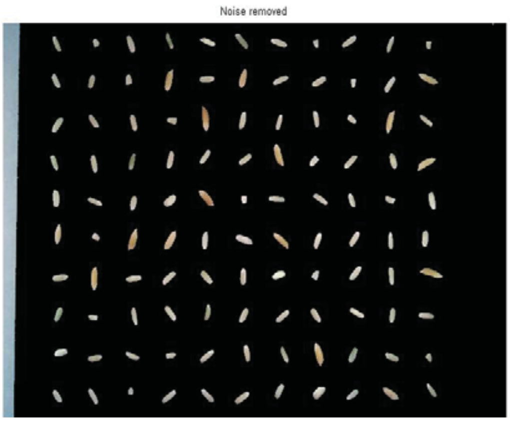
Since there might be white particles (dust) in the image, complicating the calculations, the algorithm first removes all particles smaller than 35 pixels (a quarter of a whole kernel) and then, using MATLAB commands, the number of broken kernels (K) is calculated. Hereto, in the algorithm, all processes are performed in the color space. First, the image is converted to the class of double and RGB color values are separated. Once the background is removed (with thresholding on red color data), the B/R color ratio is calculated by thresholding (the 0.75 value in Fig. 5), based on which, paddies are detected and removed from the image. In this part of the algorithm, if there is more than one kernel of rice or paddy on any hole of the kernel holding surface, it is removed and only the holes holding a single kernel are considered. This phenomenon was minimized by adjusting the suction force. Then head brown and green rice kernels (Z) were counted, and the percentage of rice breakage was calculated using equation (1).

$$\text{Percent rice breakage } F = (K / (K + Z)) \times 100 \quad (1)$$

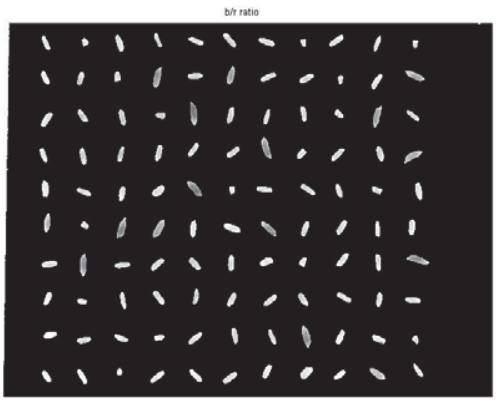
Given that the total number of paddy and head rice kernels (C) was calculated at the beginning of the algorithm, the percentage of paddy husking was calculated using (2):

$$\text{Paddy husking percentage } S = (Z / C) \times 100 \quad (2)$$

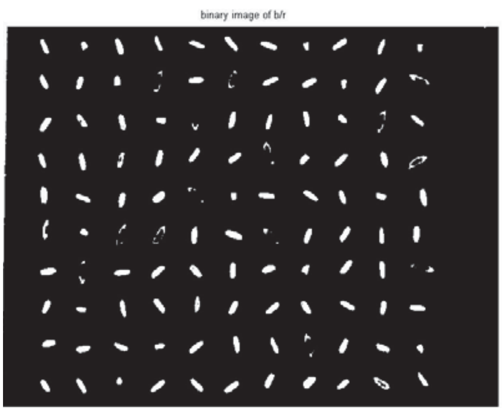
In order to evaluate the image processing algorithm, a small sample of paddy, head rice and broken brown kernels along with green rice was manually placed on the holding surface holes. An image was taken, and the image file was created. The algorithm was executed in MATLAB to calculate paddy husking percentage (S) and rice breakage (F). Various stages of image processing for this sample are shown in Fig. 8. Paddy husking and rice breakage percentage were 85.42% and 15.46%, respectively. In order to determine the accuracy of the automatic system in calculating these indices, the number of paddy and rice kernels in the image were counted manually. It was found that the number of paddy, head and broken rice kernels were 15, 79 and 16, respectively. Therefore, paddy husking percentage was 84.04% and rice breakage percentage was 16.84% which are very close to the values obtained by the automatic system. Thus, accuracy of the system in determining husking efficiency and kernel damage count was 98.36% and 91.81%, respectively.



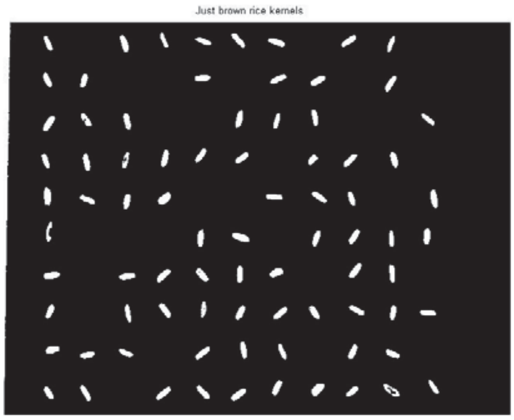
(a)



(b)



(c)



(d)

Fig. 8 Paddy and rice kernels at various stages of image processing (a) Noise removed, (b) b/r ratio, (c) Binary image of b/r, (d) Just brown rice kernels

Whole-system evaluation results are presented in Tables III and IV which shows that the average accuracy of the algorithm in calculating rice breakage and paddy husking percentages was 93.72% and 99.16 %, respectively.

TABLE III
WHOLE-SYSTEM BREAKAGE EVALUATION RESULTS

Replication	Actual breakage (%)	Automatically-Determined breakage (%)	Accuracy (breakage) (%)
1	12.12	12.5	96.86
2	16	14.58	91.13
3	16.28	17.39	93.18
Average			93.72

TABLE IV
WHOLE-SYSTEM HUSKING EVALUATION RESULTS

Replication	Actual husking (%)	Automatically-determined husking (%)	Accuracy (husking) (%)
1	87.88	88.73	99.03
2	80.77	80.39	99.53
3	80	80.85	98.93
Average			99.16

TABLE V
RESULTS FOR THE EVALUATION OF THE SUCTION SYSTEM AT THREE SUCTION LEVELS

Suction Level (mmHg)	A	B	C	D	E
-35 to -40	86	67	19	22.1	77.9
-45 to -50	91	74	17	18.7	81.3
-55 to -60	102	77	25	24.5	75.5

A= Total number of kernels held against the suction surface, B= Total number of singulated kernels, C= Total number of non-singulated kernels, D= Percentage of non-singulated kernels, E= Percentage of Singulated kernels.

To evaluate the suction system, a small amount of paddy, head, and broken rice kernels were poured onto the kernel-holding surface and the system performance was determined at three suction levels (-35 to -40 mmHg, -45 to -50 mmHg and -55 to -60 mmHg). For this purpose, the total number of kernels held against the KHS, the separated grains and the grains held together in one hole were counted, and their percentages were calculated. The results are presented in

Table V, which show that -45 mmHg to -50 mmHg suction level performed better (81.3%) than the other two levels.

IV. CONCLUSIONS

A machine-vision-based kernel characterization system was developed and tested for rice. Test results showed that the image processing method can be used for calculating percentages of paddy husking and rice breakage. The singulation unit used a tilting vacuum-operated kernel holding surface which was effective in separating the kernels to avoid overlap in the image. Overall accuracy in the automatic determination of paddy husking and rice breakage by the developed system were 99.16% and 93.72%, respectively. The system along with the kernel identification algorithm can be utilized in automatic control systems aimed at optimization of rice husking operation.

REFERENCES

[1] M. H. Payman, T. Tavakkoli Hashtjin, and S. Minaei, “Determining the distance between the rollers in rubber roller dehuskers for milling of three popular varieties of rice in Gilan province,” J. Agric. Sci., 1999, vol. 20, pp. 37- 48.

[2] N. Sakai, S. Yonekawa, and A. Matsuzaki, “Two-dimensional image analysis of the shape of rice and its application to separating varieties,” J. Food Engng, 1996, vol. 27, pp. 397-407.

[3] W. Liu, Y. Tao, T. J. Sieben morgen, and H. Chen, “Digital image analysis method for rapid measurement of rice degree of milling,” Cereal Chem., 1998, vol. 75, no. 3, pp. 380-385.

[4] B. J. Lloyd, A. G. Cnossen, and T. J. Sieben morgen, “Evaluation of two methods for separating head rice from brokens for head rice yield determination,” Applied Eng. in Agric., 2001, vol. 17, no. 5, pp. 643-648.

[5] Y. N. Wan, C. M. Lin, and J. F. Chiou, “Rice quality classification using an automatic grain quality inspection system,” Trans. *ASAE*, 2002, vol. 45, no. 2, pp. 379–387.

[6] M. Tanska, D. Rotkiewicz, W. Kozirok, and I. Konopka, “Measurement of the geometrical features and surface color of rapeseeds using digital image analysis,” Food Res. Inter., 2005, vol. 38, pp. 741-750.

[7] S. Kiani, and A. Jafari, “Crop Detection and Positioning in the Field Using Discriminant Analysis and Neural Networks Based on Shape Features,” J. Agr. Sci. Tech., 2012, vol. 14, pp. 755-765.

[8] I. Golpour, R. Amiri Chayjan, J. Amiri Parian, and J. Khazaei, “Prediction of paddy moisture content during thin layer drying using machine vision and artificial neural networks,” J. Agr. Sci. Tech., 2015, vol. 17, pp. 287-298.

[9] H. J. Shei, and C. S. Lin, “An optical automatic measurement method for the moisture content of rough rice using image processing techniques,” Com. and Elec. in Agric., 2012, vol. 85, pp. 134-139.

[10] Q. Yao, D. X. Xian, Q. J. Liu, B. J. Yang, G. Q. Diao, and J. Tang, “Automated counting of rice planthoppers in paddy fields based on image processing,” J. Integ. Agric., 2014, vol. 13, no. 8, pp. 1736-1745.

[11] C. Sun, T. Liu, C. Ji, M. Jiang, T. Tian, D. Guo, L. Wang, Y. Chen, and X. Liang, “Evaluation and analysis the chalkiness of connected rice kernels based on image processing technology and support vector machine,” J. Cereal Sci., 2014, vol. 60, no. 2, pp. 426-432.

[12] S. Taghadomi-Saberi, M. Omid, Z. Emam-Djomeh, and Kh. Faraji-Mahyari, “Determination of Cherry Color Parameters during Ripening by Artificial Neural Network Assisted Image Processing Technique,” J. Agr. Sci. Tech., 2015, vol. 17, pp. 589-600.