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Development of an expert vision-based system for inspecting rice quality indices

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RESEARCH ARTICLE

Abstract

In this study, a computer vision system comprising of a special rice tray, scanner, and computer-aided processing software was developed to assess rice appearance quality. The applicability of the system was evaluated for assessment of four rice varieties. Rice grains were accurately (>98%) classified into whole and broken kernels regarding their dimensional features estimated precisely with coefficient of determination (R^2) of more than 98% and root mean squared error of 0.08. Optimal thresholding on the vertical coefficient of wavelet transform resulted in fissure detection with an accuracy of 96.51%. Red and black spots of the rice kernels were also precisely detected by thresholding on the red colour difference and gray-scale components respectively. Results indicated that very high accuracies (R^2 about 99%) were obtained for whiteness and chalkiness measurements. It was concluded that the image processing technique has a significant potential to be applied for appearance quality assessment of rice kernels.

Keywords: rice inspection, image analysis, colour processing, wavelet transform, defect detection

1. Introduction

Rice (*Oryza sativa* L.) as the staple food in the diet after wheat, is one of the oldest and most important crops cultivated in many parts of the world. According to the Food and Agriculture Organization, the global rice paddy production increased largely from less than 599 million tonnes in 2000 to about 741 million tonnes in 2014. At the same period, the total paddy production of Iran reached from 1.97 million tonnes to 2.6 million tonnes (http://faostat.fao.org).

Several factors such as seed variety, growing condition, possible damages during harvesting operations, and postharvest processes (e.g. drying and milling) might impact rice appearance characteristics which are important in the product price and marketability.

Currently, rice quality is assessed manually and by visual inspection which is very effective but time consuming, tedious and expensive. Also the results can be seriously affected by the physical and mental state of visitors such as fatigue, improper eyesight, lack of experience or lack of impartiality. Considering the above restrictions, it is needed to seek better solutions for easy and effective rice quality inspection operation.

Machine vision as one of the new systems applied in measuring the quality indices and grading of agricultural products, has been more accepted by users because of its indirect and non-destructive nature. Several applications of machine vision and image processing techniques have been studied in various aspects of post-harvest and food processing (Brescia *et al.*, 2007; Dehrouyeh *et al.*, 2010; Dutta *et al.*, 2015; Hosseinpour *et al.*, 2014; Jia *et al.*, 2012; Kiani and Minaei, 2016).

Also, there are many investigations conducted on the use of image processing methods for classification, quality assessment and grading of agricultural grains (Dubosclard *et al.*, 2015; Mebatsion *et al.*, 2013; Pearson, 2009; Shouche *et al.*, 2001; Vithu and Moses, 2016; Zapotoczny *et al.*, 2008).

Integrating the capabilities of image processing algorithms into the areas relating to paddy and rice has been interested by researchers. Huang *et al.* (2013) developed an automatic measurement of rice panicle length based on dual-camera imaging. Another application of image processing was revealed by Wang *et al.* (2013) for measuring the rice leaf nitrogen status using colour thresholding method. Azman *et al.* (2014) estimated the maturity level of paddy using various colour indices extracted from the RGB (red-green-blue) colour space. Kuo *et al.* (2016) succeed to distinguish the rice grains of 30 varieties using morphological, textural and colour characteristics extracted from paddy images. Several other studies have been carried out in this field by Shei and Lin (2012), Golpour *et al.* (2014), Anami *et al.* (2015), Chaugule and Mali (2014) and Zareiforoush *et al.* (2016b) to name just few.

Rice appearance quality is the most important trait in rice production because it influences customer selection when buying rice (Yun *et al.*, 2015). Visual characteristics of milled rice, namely colour, dimensions, head rice, chalky or stained rice grains, broken rice, and milling rate of rice, etc., are very important parameters for determining the apparent quality of whitened rice.

The automatic system using combination of near-infrared transmission instrument and a visible light segregator was developed to determine moisture, protein content, and sound whole kernel ratio of rice (Kawamura *et al.*, 2003).

Image analysis algorithms were used by Yadav and Jindal (2001) for measuring dimensional features and gray level distribution of rice kernels to determine head rice and milling rate of milled rice. They reported an accuracy of 99% between image-extracted values and experimental ones. An automatic system relying on the machine vision was also developed by Yao *et al.* (2009) to evaluate rice chalkiness and shape including length, width and aspect ratio. Another study was conducted by Wan *et al.* (2010) to investigate the effect of each unit operation during the milling process on the changes of rice colour.

A computer based intelligent system was developed by Zareiforoush *et al.* (2015) for qualitative grading of milled rice based on two indices, namely degree of milling and percentage of broken kernels. Results of analysis showed 89.8% agreement between the grading results obtained from their developed system and those determined by the experts. They also in another research applied size, shape and colour features and different metaheuristic clustering techniques to classify milled grains. Their results indicated that artificial neural network was the most reliable classifier with the accuracy of 98.72% (Zareiforoush *et al.*, 2016a).

According to literature review, although there are some researches on the application of image processing techniques to extract appearance characteristics of rice kernels, but most of previous works were not such comprehensive and were limited only to article publication. There has been almost no research conducted focusing on the development of a practical system based on computer vision for comprehensive inspecting of the milled rice quality indices. Such system can be used in rice processing factories in order to verify the quality parameters of the final product and to assess the performance of processing devices (e.g. dryer and milling machine). Also, it can be used simply by researchers to characterise new rice varieties or to evaluate the effects of their desired treatments – in the rice production stages from growing to post harvest processing operations – on the characteristics of milled rice. Evaluating the possibility of such system was the main objective of this study.

2. Materials and methods

System design

Figure 1 shows the computer vision based rice inspection system developed in this study. The main components of system were:

1. scanner;
2. suitable frame and rice tray;
3. processing unit (including processor and developed algorithm);
4. user graphical interface.

After investigation among available scanners, a handy scanner was selected. The specifications of the scanner are presented in Table 1.

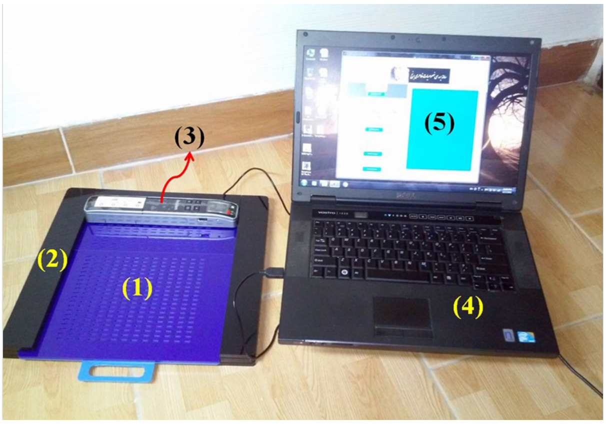

Figure 1. Developed rice inspection system: (1) rice tray; (2) frame; (3) scanner; (4) laptop processor; and (5) processing software.

Table 1. Scanner characteristics.

Variable	Description
Model	MiWand 2, Avision (Tehran, Iran)
Maximum document size	216×356 mm
Image type	JPEG
Resolution	1,200 dpi
Colour depth	24 bit true colour

Grain tray was a dark blue Plexiglas plate surface evenly indented to the depth of 3 mm. The tray had two sections. To access apparent attributes (e.g. length, width, colour characteristics, breakage, etc.), grains were distributed on the main section of the tray. This section was meshed with 9×2.3 mm holes allowing grains to separately lie on their back in the provided indents.

The indents on the other section of the tray were narrower and had widths varying from 1.4 mm to 1.8 mm, which caused the grains to fall in the holes on their edge. So the thickness of grains could be measured.

Processing algorithm

Flowcharts in Figure 2 and 3, respectively, illustrate the summary of several steps performed for segmenting the images and extracting rice apparent feature. Since the seed tray was chosen from dark blue colour, the red and green component values were very low in the image background (tray) unlike the pixels of desired objects (rice kernels) where all three components had high values. Therefore, simply by applying optimal threshold on the contrast-enhanced red colour component using Otsu technique (Otsu, 1979), background regions were separated from rice grains accurately. After removing unwanted parts by

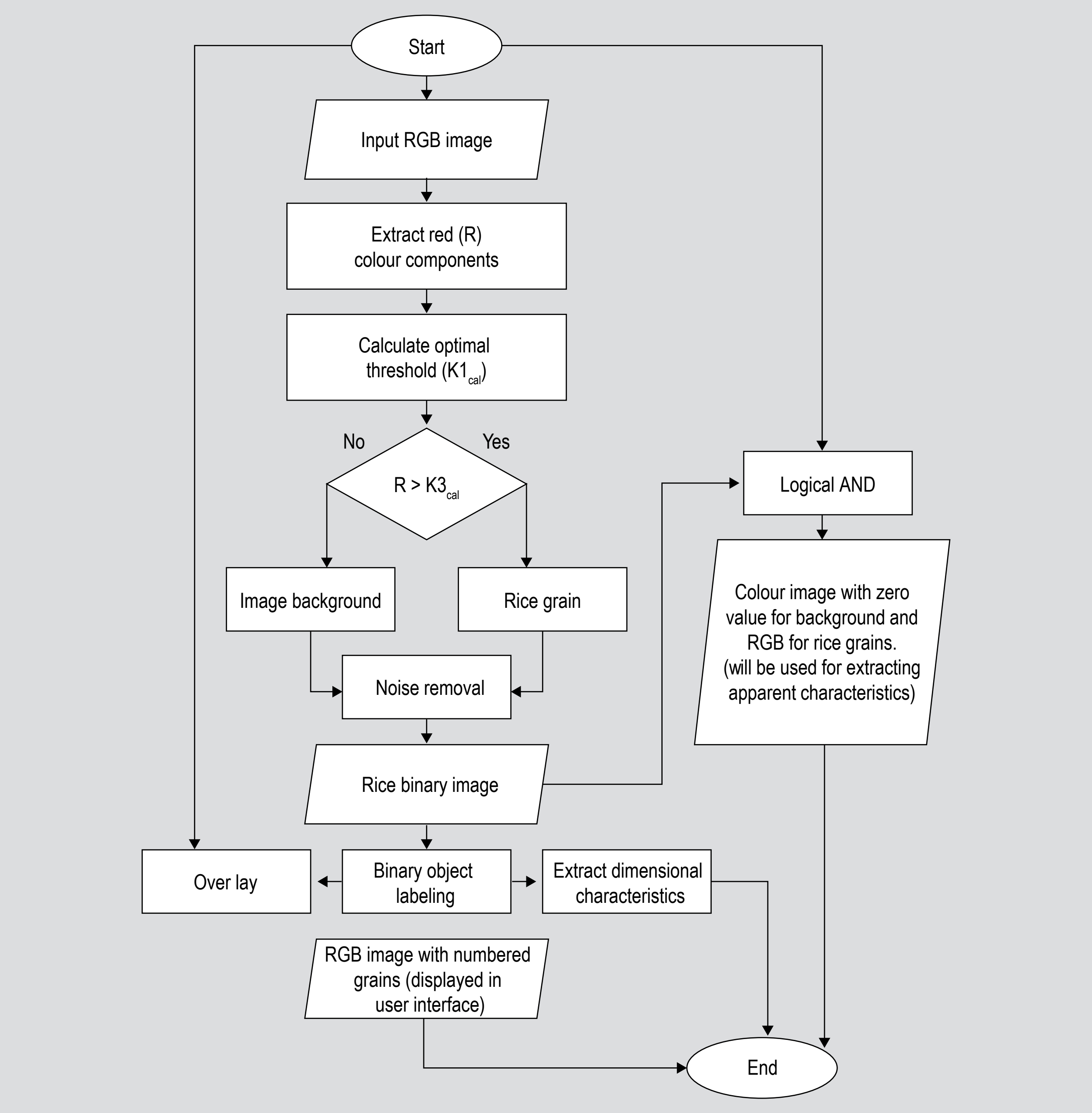

Figure 2. Flowchart of operations performed for rice image segmentation and dimension extraction.

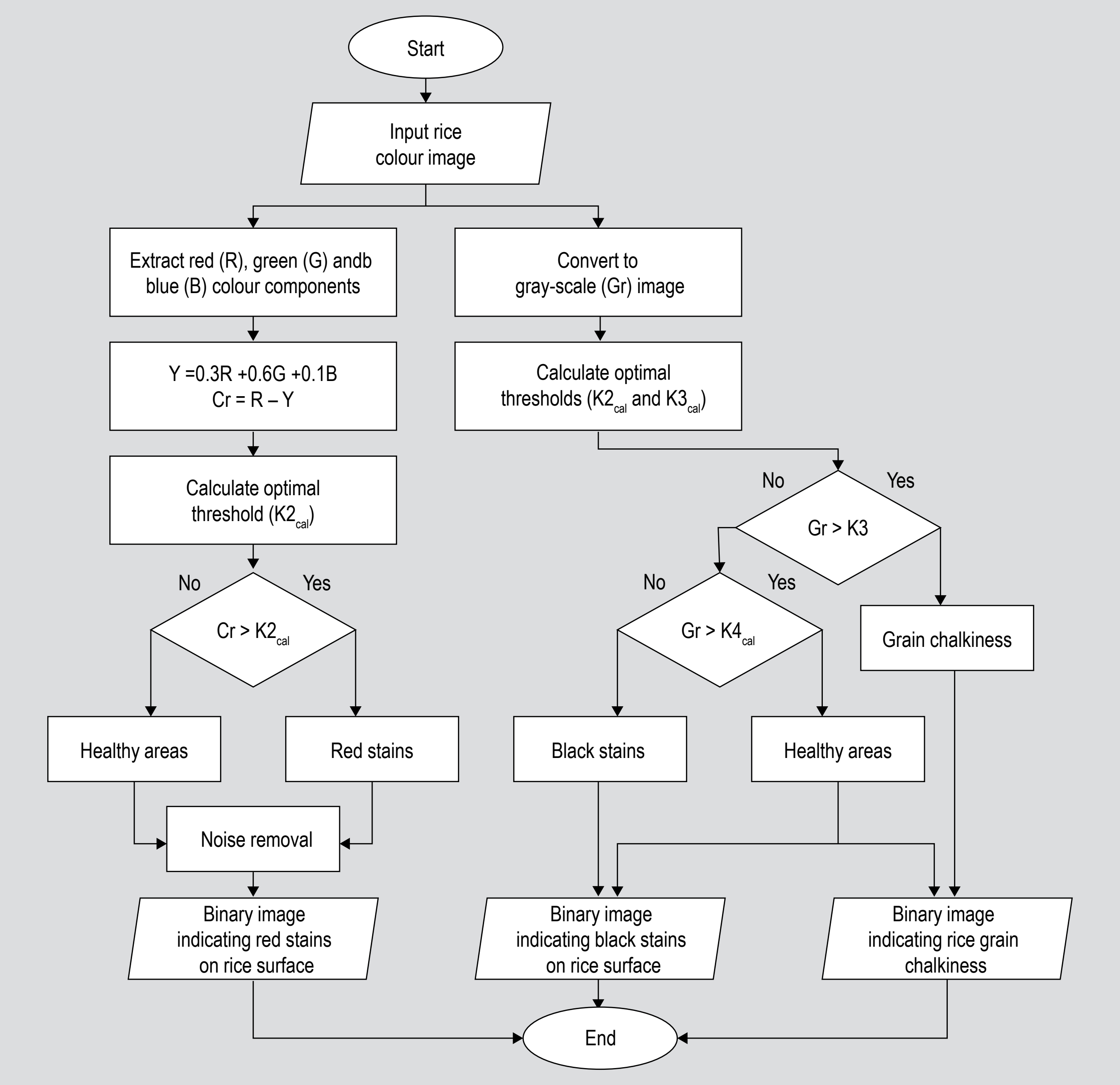

Figure 3. Flowchart of operations performed to detect red and black stains and chalkiness on rice kernels.

applying morphological opening, the regions of interest were labelled in the resulting binary image and were used for further operations. The resulting images of several stages of segmentation process for a single grain are shown in Figure 4.

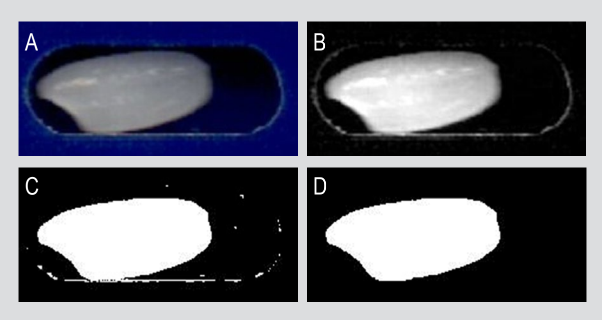

Figure 4. Several steps of the segmentation process: (A) original colour image; (B) contrast-enhanced red colour component; (C) first binary result of segmentation; and (D) final binary image of rice kernels after removing unwanted parts and filling probable holes inside the object.

Surface area and main dimensions of grains were determined by extracting 'Area,' 'MajorAxis-Length' and 'MinorAxis-Length' features by applying the 'regionprops' function in the processing software (MATLAB R2013a; MathWorks, Natick, MA, USA).

Dimensional classification of rice kernels was performed according to the standard provided by the Institute of Standards and Industrial Research of Iran (ISIRI, 2012) where the kernels, regarding their dimensions, were divided to two main groups namely whole kernels and broken ones. Broken kernels were considered as rice grains that have the length less than three-fourths of whole rice kernel (ISIRI, 2012).

To extract colour dependent characteristics such as milling rate and spots, logical AND was applied between the primary RGB image of each grain and its binary image. So the colour images of grains with absolute zero value for background pixels were resulted.

It was revealed by Sun *et al.* (2014) that chalky areas of grains can be clearly segmented in the grayscale images. Also the application of grayscale image for determining the rice milling rate is reported in literatures (Yadav and Jindal, 2001; Zareiforoush *et al.*, 2015). Therefore the chalkiness of grains may change the results of milling rate measurement. Also existence of black and red spots on the grain surface can affect the results of grain milling rate estimations. In order to avoid from negative effects of the presence of stains and chalky regions on the whiteness measurement results, the milling rate of kernels was measured from pixels of other than chalky or spot regions.

Forasmuch as there was a distinct colour difference between areas with red spots and other areas of the rice image, the red spots on the surface or rice grains were detected by optimal thresholding (Otsu, 1979) on the red colour difference (Cr) in YCrCb colour space. Equations 1 and 2 convert RGB space to YCrCb space and extract Cr colour component respectively (Bulanon *et al.*, 2002):

$$Y = 0.3R + 0.6G + 0.1B \tag{1}$$

$$C_r = R - Y \tag{2}$$

Where, R, G and B are red, green and blue colour intensity values, and Y is luminance. Red kernels were those that more than a quarter of their surface was red stained (ISIRI, 2012).

Our pre-experiments revealed that the gray-level intensities of black stains were distinctly less than those of poorly milled grains. So, black stains and chalky areas were detected in the gray-scale images of rice kernels by using low-pass and high-pass thresholding respectively. Areas with any stains as well as those with chalkiness were excluded from kernel milling rate calculations.

In order to achieve different whiteness levels, paddy grains were manually dehusked and the obtained brown rice kernels were polished using a laboratory abrasive type whitener (model JNMS15; Satake, Hiroshima, Japan) at different whitening durations to prepare samples of different degrees of milling. The milling tare of kernels was measured using a digital whiteness meter (model C-300; Kett, Tokyo, Japan). Images of kernels with different whiteness levels were captured and converted from RGB colour space to HSV (hue, saturation, value) one (Mandavi and Nagwanshi, 2015). The whiteness values were obtained by calibrating the value component with experimental milling rate results.

In the other section of algorithm, two-dimensional discrete wavelet transform approach was used to find fissures in milled rice kernels. One-level Haar wavelet decomposition was applied on the contrast-enhanced gray-scale images of kernels.

Considering that fissures in the rice grains are generally perpendicular to the main axis, vertical wavelet coefficient (LH sub band) image was extracted and converted to binary image by Otsu thresholding. White pixels relating to boundaries and spots were removed from resulting binary image. The remaining unwanted objects were omitted using morphological opening function to achieve final binary image indicating rice kernel fissures.

User graphical interface

Figure 5A shows the main window of the system. This window provides the ability to load the prepared image, enables the user to monitor all seeds or inspect a particular seed by entering its number, and to save the extracted data in a excel worksheet.

In another window shown in Figure 5B, a summary of the characteristics extracted from rice seeds is displayed for the user. The mean and standard deviation of length, width and thickness of seeds, the number and percentage of stained, fissured, and chalky seeds, and the average aspect ratio and roundness values of whole kernels are of the information indicated in this window. Also the numbers and percentages of seeds that are dimensionally classified into groups according to ISIRI are reported in this window.

Characteristics of selected single rice kernels are also presented in another window shown in Figure 5A. In addition, the binary images of probable defects such as stain, fissures and chalkiness are displayed for the selected grain.

Accuracy assessment

To assess the size measurement accuracy of the device, samples containing 60 whole kernels and 40 broken ones were manually selected from each of the four common rice varieties in north of Iran namely Hashemi, Anbarboo, Dom-zard and Jamshidi. More details about deficiencies in the samples are presented in Table 2. The kernels were visually assessed to measure dimensions, defects and appearance characteristics. The samples were then processed by the developed device and results of the device

SUMMARIZED CHARACTERISTICS OF GRAINS

Total Number of Grains 104

Dimensional Classification (ISIRI)

	Number	Percent
Whole Kernel	86	82.6923
Very Long	12	11.5385
Long	60	57.6923
Medium	14	13.4615
Short	0	0
Broken Kernel	18	17.3077
Head Rice	5	4.8077
Large Broken	11	10.5769
Medium Broken	2	1.9231
Small Broken	0	0
Chips	0	0

Dimensional Characteristics

	Average	Std.
Length (mm)	7.1495	0.35078
Width (mm)	1.9772	0.20124
Thickness (mm)	1.5422	0.095937

Appearance Characteristics

	Number	Percent
Chalky Grains	3	3.4884
Red Stained Grains	0	0
Black Stained Grains	0	0
Green Grains	0	0
Brown or Not-Milled Grais	5	5.814
Cracked Grains	7	6.7308

Average Roundness 0.2697

Aveeage Aspect Ratio 3.6509

Figure 5. Graphical user interface windows of rice inspection device: (A) main window; (B) summary of all grains characteristics window. The dimensional classification was based on ISIRI (2012).

were compared with the manually extracted ones to evaluate the performance of the rice inspection device.

T-test was used to determine if there is a significant difference between experimental and vision-based results. Also two criteria were calculated and considered, to

Table 2. Number of each variety samples used for development and assessment of algorithms.

Operation	Number of samples used for	
	Algorithm development	Algorithm assessment
Dimensions measurement	10	50
Broken kernel detection	10	30
Fissure detection	5	20
Chalkiness detection	5	20
Red spot detection	5	20
Black spot detection	5	20

compare the performances of the developed algorithms. The coefficient of determination was computed by:

$$R^2 = \left[1 - \frac{\sum_{i=1}^{N} (Y_{Exp,i} - Y_{Pre,i})^2}{\sum_{i=1}^{N} (Y_{Exp,j} - \overline{Y}_{Exp})^2} \right] \times 100 \qquad (3)$$

The root means square error (RMSE) was determined by:

$$RMSE = \left[\frac{1}{N} \sum_{i=1}^{N} (Y_{Exp,i} - Y_{Pre,i})^2 \right]^{0.5} \qquad (4)$$

Where, $Y_{Exp,i}$ $Y_{pre,i}$ are respectively the ith experimental and predicted data from N total data.

3. Results and discussion

To evaluate the reliability of the developed device, the accuracy parameters were measured on the test samples. Table 3 shows R^2, RMSE, and significance values of t-test between dimensions of samples estimated by the developed device and those measured manually using a digital calliper with a sensitivity of 0.01 mm. Regarding the performance values shown in Table 3, there were strong similarities observed between measured and estimated values for determination of grain dimensions in all studied varieties which reflect the high accuracy and reliability of the device.

To assess the goodness of measured data vs experimental ones, the residual errors of the developed system for measuring grain dimensions were extracted. Residuals of algorithm for length measurement are plotted in Figure 6 which shows that the errors are very small and negligible which in turn clearly depicts the robustness of the developed algorithm determining the size of rice kernels. This high accuracy is very important since the extracted features are used for further operations such as grain dimensional classification and detecting whole and broken kernels.

These results were much more accurate that those obtained by Sansomboonsuk and Afzulpurkar (2006) however the main object of their study was to separate touching kernels. This problem was simply solved in this study by using a special tray to singulate kernels before taking images.

Table 3. Average values of measured and estimated dimensions for studied rice varieties and performance criteria of rice inspection device for dimension measurement.[1]

Dimension	Criteria	Hashemi	Anbarboo	Dom-zard	Jamshidi	All varieties
Length	Measured (mm)	7.352	6.028	7.035	7.338	–
	Estimated (mm)	7.356	6.014	7.027	7.338	–
	R^2 (%)	98.94	99.06	99.03	98.97	98.99
	RMSE	0.064	0.061	0.062	0.064	0.063
	Sig. (two tailed)	0.761	0.787	0.769	0.763	0.770
Width	Measured (mm)	1.995	1.956	2.011	2.261	–
	Estimated (mm)	1.992	1.960	2.008	2.262	–
	R^2 (%)	98.46	98.51	98.46	98.48	98.47
	RMSE	0.085	0.081	0.086	0.085	0.086
	Sig. (two tailed)	0.689	0.681	0.679	0.691	0.686
Thickness	Measured (mm)	1.631	1.642	1.551	1.637	–
	Estimated (mm)	1.636	1.647	1.557	1.641	–
	R^2 (%)	98.63	98.71	98.63	98.79	98.70
	RMSE	0.078	0.069	0.080	0.069	0.072
	Sig. (two tailed)	0.677	0.675	0.678	0.678	0.677

[1] RMSE = root means square error; R^2 = coefficient of determination.

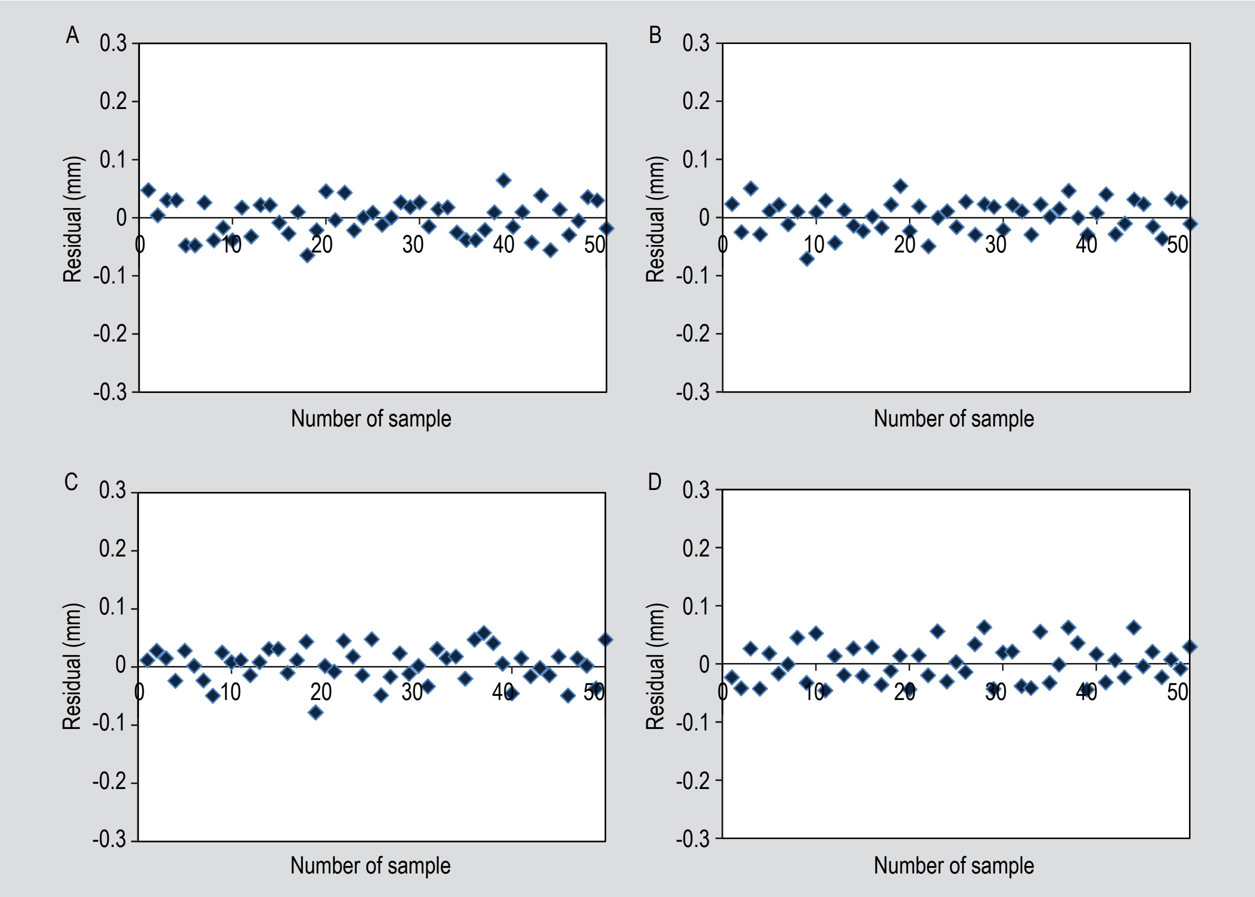

Figure 6. Distribution of error of measuring length of rice kernels: (A) Hashemi; (B) Anbarboo; (C) Dom-zard; and (D) Jamshidi.

Images of several steps of red spot detection algorithm are shown in Figure 7. Also the image of a sample result of chalkiness detection algorithm is shown in Figure 8.

Spots and chalkiness measurement results of the developed system were compared to experimental data and showed high level of accordance. R^2 and RMSE values between experimental and image based measurements are revealed in Table 4.

Sun *et al.* (2014) used image analysis in order to detect rice chalkiness accurately. Detection of spots has not been reported in literature. Detection of spots is important for quality assessment. Additionally these spots can affect the results of some other detective algorithms such as milling rate estimation and crack detection ones.

Figure 9 shows images resulted from several steps of fissure detection algorithm. Applying optimal threshold on the HL subband of wavelet transform (vertical wavelet coefficient) of the rice images resulted in successfully detection of rice fissures.

To evaluate the performance of system in the detection of fissured and broken kernels, two criteria namely correct detection rate (CDR) and wrong detection rate (WDR) values were defined as follows:

$$\text{CDR} = \frac{\text{number of broken/ cracked kernels correctly detected}}{\text{actual number of broken/ cracked kernels}} \times 100 \qquad (5)$$

$$\text{WDR} = \frac{\text{number of healthy kernels mistakenly detected as broken/cracked}}{\text{actual number of broken/ cracked kernels}} \times 100 \qquad (6)$$

The results are presented in Table 5 which shows the reliability of the developed system for detection of broken kernels.

These results were also more reliable that those reported by Verma (2010) for grading and categorisation of three Indian rice varieties where the results were not accurate because the developed system lacked proper illumination. The illumination problem was solved in this study by using a scanner for taking images.

Table 4. Performance criteria of rice inspection device for defect assessment.[1]

Characteristic	Criteria	Hashemi	Anbarboo	Dom-zard	Jamshidi
Red spot	R^2 (%)	98.69	98.70	98.67	98.72
	RMSE	0.070	0.070	0.071	0.068
Black spot	R^2 (%)	98.74	98.71	98.70	98.69
	RMSE	0.066	0.070	0.068	0.070
Chalkiness	R^2 (%)	98.85	98.91	98.88	98.88
	RMSE	0.063	0.059	0.062	0.060

[1] RMSE = root means square error; R^2 = coefficient of determination.

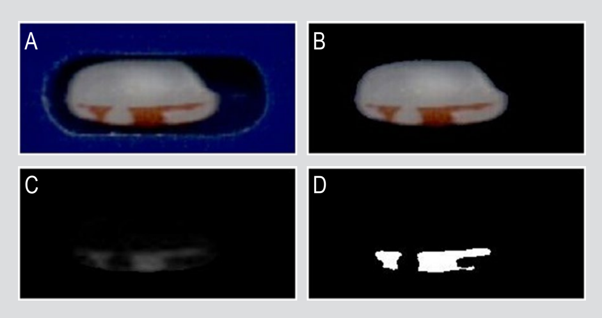

Figure 7. Several steps of red spot detection process: (A) original colour image; (B) colour image resulting from applying logical AND between the original colour image and rice segmented image; (C) Cr colour component extracted from Figure 7B; and (D) binary image showing red spots.

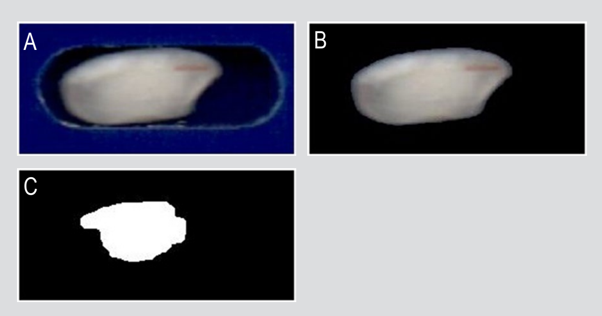

Figure 8. Sample result of chalkiness detection: (A) original RGB image; (B) after applying logical and between colour image and segmented image of rice; (C) binary image showing chalky areas.

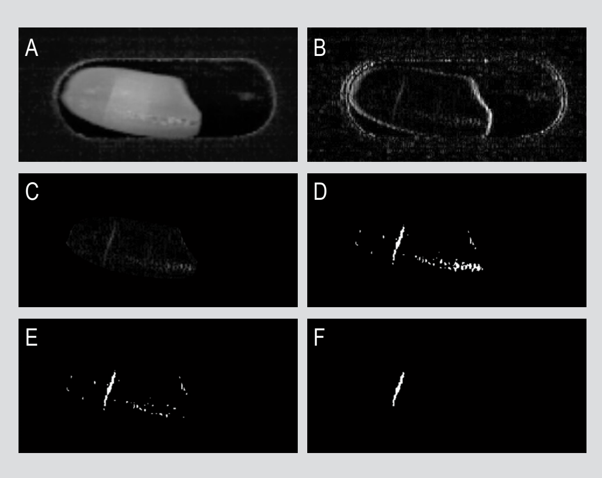

Figure 9. (A) gray-scale image of rice; (B) vertical wavelet subband of Figure 9A; (C) after applying logical AND between binary image of rice and Figure 9B; (D) after applying optimal threshold on Figure 9C; (E) after removing spot areas; (F) after removing small objects (showing fissures).

Table 5. Results of the rice inspection system for fissured and broken kernel detection.[1]

Characteristic	Fissure		Breakage	
Criteria	CDR (%)	WDR (%)	CDR (%)	WDR (%)
	96.51	2.35	98.86	4.69

1 CDR = correct detection rate; WDR = wrong detection rate.

Fissures were also detected accurately in this study by applying optimal threshold on the vertical wavelet coefficient image. That was more accurate than that achieved by Courtois *et al.* (2010) where they used watershed algorithm for fissure detection as the wavelet coefficients are good descriptors of directional variations in the images. Crack detection was also performed in x-ray images of paddy by applying thresholds on intensity images (Lakshmi *et al.*, 2016). Although cost and throughput speed of x-ray imaging would seem to eliminate it as a practical method (Haff and Toyofuku, 2008).

The accuracy of developed system was also evaluated for estimating milling rate of rice grains among 100 kernels with different milling rates. The R^2 and RMSE values were obtained to be 98.91% and 0.063, respectively, for milling rate estimation. The experimental vs estimated milling rates are presented in Figure 10.

Yadav and Jindal (2001) successfully applied mean gray level of kernel surface for accessing the milling rate of 10 Thai rice varieties. However their study was performed on non-defected grains and the effect of spots and defects on the rice surfaces was not taken into account.

Strong agreements were observed between experimental and vision based estimated characteristics, suggesting the feasibility of using the developed system for evaluating apparent quality of rice kernels.

The results obtained in this study conform to some of those of other literature (Ajay *et al.*, 2013; Chen *et al.*, 2012; Gudipalli *et al.*, 2016; Yao *et al.*, 2009) which indicates the high potential of machine vision systems for evaluation of rice features, but it must be mentioned that most of these researches are limited to measuring kernel dimensions and estimating the whole and broken kernels based on size. Few researches have been also conducted to identify other parameters such as fissures and of chalkiness. The main advantage of this study was that the developed system was capable to accurately inspect almost all important qualitative characteristics of rice kernels.

This system, by collecting the most important quality indicators with high measurement accuracy, can be confidently applied in commercial markets and product processing plants for appearance quality assessment of rice. Such comprehensive and reliable algorithm was not reported in literature.

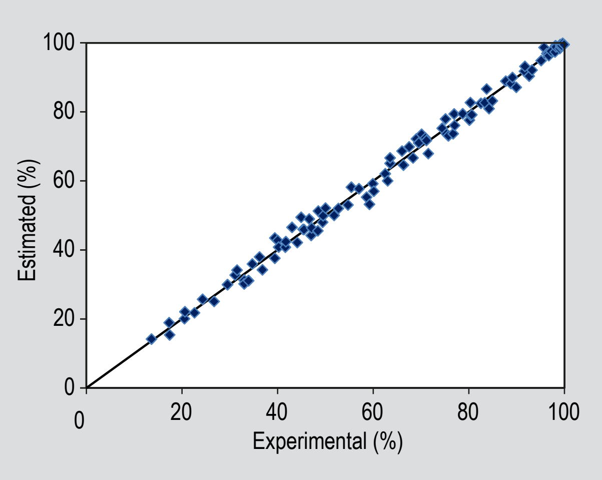

Figure 10. Estimated vs experimental values of rice milling rates.

4. Conclusions

In this study, a heuristic system was developed based on machine vision technique to investigate the feasibility of determining the quality and appearance characteristics of rice. Several important parameters including dimensions, chalkiness, and defects were inspected by applying image processing algorithms. Results revealed the accuracy of image based techniques were more than 98% for estimating all desired features except for identifying fissures (>96%). It was concluded that image processing is a reliable method for rice inspection operation.

Preparing a fast and reliable method for rice appearance quality assessment is one of the most important problems associated with rice industry. It seems that the system constructed in this research, the idea behind it, and the described methodologies can be effectively employed for developing and enhancing rice quality assessment operation which is a prominent part of the rice industry.

References

Ajay, G., Suneel, M., Kumar, K.K. and Prasad, P.S., 2013. Quality evaluation of rice grains using morphological methods. International Journal of Soft Computing and Engineering 2: 35-37.

Anami, B.S., Naveen, N. and Hanamaratti, N., 2015. Behavior of HSI color co-occurrence features in variety recognition from bulk paddy grain image samples. International Journal of Signal Processing, Image Processing and Pattern Recognition 8: 19-30.

Azman, N., Bejo, S.K., Ismail, W., Ishak, W. and Wayayok, A., 2014. Estimating maturity of paddy using RGB colour space. Journal of Advanced Agricultural Technologies 1: 119-124.

Brescia, M.A., Sacco, D., Sgaramella, A., Pasqualone, A., Simeone, R., Peri, G. and Sacco, A., 2007. Characterisation of different typical Italian breads by means of traditional, spectroscopic and image analyses. Food Chemistry 104: 429-438.

Bulanon, D., Kataoka, T., Ota, Y. and Hiroma, T., 2002. AE–automation and emerging technologies: a segmentation algorithm for the automatic recognition of Fuji apples at harvest. Biosystems Engineering 83: 405-412.

Chaugule, A. and Mali, S.N., 2014. Evaluation of texture and shape features for classification of four paddy varieties. Journal of Engineering 2014, Article ID: 617263.

Chen, X., Ke, S., Wang, L., Xu, H. and Chen, W., 2012. Classification of rice appearance quality based on LS-SVM using machine vision. In: Liu, C., Wang, L. and Yang, A. (eds) Information Computing and Applications, ICICA 2012. Communications in Computer and Information Science, volume 307. Springer Verlag, Berlin, Germany, pp. 104-109.

Courtois, F., Faessel, M. and Bonazzi, C., 2010. Assessing breakage and cracks of parboiled rice kernels by image analysis techniques. Food control 21: 567-572.

Dehrouyeh, M., Omid, M., Ahmadi, H., Mohtasebi, S. and Jamzad, M., 2010. Grading and quality inspection of defected eggs using machine vision. International Journal of Advanced Science and Technology 17: 23-31.

Dubosclard, P., Larnier, S., Konik, H., Herbulot, A. and Devy, M., 2015. Automated visual grading of grain kernels by machine vision. In: Meriaudeau, F. and Aubreton, O. (eds.). Proceedings Volume 9534 of the 12th International Conference on Quality Control by Artificial Vision 2015, Le Creusot, France. International Society for Optics and Photonics, Bellingham, WA, USA, 8 pp.

Dutta, M.K., Singh, A. and Ghosal, S., 2015. A computer vision based technique for identification of acrylamide in potato chips. Computers and Electronics in Agriculture 119: 40-50.

Golpour, I., Parian, J.A. and Chayjan, R.A., 2014. Identification and classification of bulk paddy, brown, and white rice cultivars with colour features extraction using image analysis and neural network. Czech Journal of Food Science 32: 280-287.

Gudipalli, A., Prabha, N.A. and Reddy Ch, P., 2016. A review on analysis and grading of rice using image processing. ARPN Journal of Engineering and Applied Sciences 11: 13550-13555.

Haff, R.P. and Toyofuku, N., 2008. X-ray detection of defects and contaminants in the food industry. Sensing and Instrumentation for Food Quality and Safety 2: 262-273.

Hosseinpour, S., Rafiee, S., Aghbashlo, M. and Mohtasebi, S.S., 2014. A novel image processing approach for in-line monitoring of visual texture during shrimp drying. Journal of Food Engineering 143: 154-166.

Huang, C., Yang, W., Duan, L., Jiang, N., Chen, G., Xiong, L. and Liu, Q., 2013. Rice panicle length measuring system based on dual-camera imaging. Computers and Electronics in Agriculture 98: 158-165.

Institute of Standards and Industrial Research of Iran (ISIRI), 2012. Rice – specifications and test methods. ISIRI, Tehran, Iran. Available at: http://standard.isiri.gov.ir.

Jia, W., Yue, Y., Fernstrom, J.D., Yao, N., Sclabassi, R.J., Fernstrom, M.H. and Sun, M., 2012. Imaged based estimation of food volume using circular referents in dietary assessment. Journal of Food Engineering 109: 76-86.

Kawamura, S., Natsuga, M., Takekura, K. and Itoh, K., 2003. Development of an automatic rice-quality inspection system. Computers and Electronics in Agriculture 40: 115-126.

Kiani, S. and Minaei, S., 2016. Potential application of machine vision technology to saffron (*Crocus sativus* L.) quality characterization. Food Chemistry 212: 392-394.

Kuo, T.-Y., Chung, C.-L., Chen, S.-Y., Lin, H.-A. and Kuo, Y.-F., 2016. Identifying rice grains using image analysis and sparse-representation-based classification. Computers and Electronics in Agriculture 127: 716-725.

Lakshmi, G., Rao, A.M. and Sachin, K., 2016. Crack detection in paddy using image processing techniques. International Journal of Scientific and Engineering Research 7: 336-339.

Mandavi, R. and Nagwanshi, K.K., 2015. Content based image retrieval and classification using principal component analysis. International Journal of Science and Research 4: 2579-2582.

Mebatsion, H., Paliwal, J. and Jayas, D., 2013. Automatic classification of non-touching cereal grains in digital images using limited morphological and color features. Computers and Electronics in Agriculture 90: 99-105.

Otsu, N., 1979. An automatic threshold selection method based on discriminate and least squares criteria. Denshi Tsushin Gakkai Ronbunshi 63: 349-356.

Pearson, T., 2009. Hardware-based image processing for high-speed inspection of grains. Computers and Electronics in Agriculture 69: 12-18.

Sansomboonsuk, S. and Afzulpurkar, N., 2006. The appropriate algorithms of image analysis for rice kernel quality evalution. In: Proceedings of the 20th Conference of Mechanical Engineering Network of Thailand, Bangkok, October 18-20, 2006, Nakhon Ratchasima, Thailand, pp. 18-20. Available at: http://me.psu.ac.th/tsme/ME_NETT20/article/pdf/amm/AMM096.pdf.

Shei, H.-J. and Lin, C.-S., 2012. An optical automatic measurement method for the moisture content of rough rice using image processing techniques. Computers and Electronics in Agriculture 85: 134-139.

Shouche, S., Rastogi, R., Bhagwat, S. and Sainis, J.K., 2001. Shape analysis of grains of Indian wheat varieties. Computers and Electronics in Agriculture 33: 55-76.

Sun, C., Liu, T., Ji, C., Jiang, M., Tian, T., Guo, D., Wang, L., Chen, Y. and Liang, X., 2014. Evaluation and analysis the chalkiness of connected rice kernels based on image processing technology and support vector machine. Journal of Cereal Science 60: 426-432.

Verma, B., 2010. Image processing techniques for grading and classification of rice. In: Computer and Communication Technology (ICCCT) 2010, International Conference on IEEE, September 17-19, 2010, Allahabad, Uttar Pradesh, India, pp. 220-223.

Vithu, P. and Moses, J., 2016. Machine vision system for food grain quality evaluation: a review. Trends in Food Science and Technology 56: 13-20.

Wan, P., Long, C. and Huang, X., 2010. A detection method of rice process quality based on the color and BP neural network. International Conference on Computer and Computing Technologies in Agriculture. In: Li, D., Liu, Y. and Chen, Y. (eds.) Computer and computing technologies in agriculture IV: 4th IFIP TC 12 Conference, CCTA 2010, Nanchang, China, October 22-25, 2010, Selected Papers, Part I. Springer, Berlin, Germany, pp. 25-34.

Wang, Y., Wang, D., Zhang, G. and Wang, J., 2013. Estimating nitrogen status of rice using the image segmentation of GR thresholding method. Field Crops Research 149: 33-39.

Yadav, B. and Jindal, V., 2001. Monitoring milling quality of rice by image analysis. Computers and Electronics in Agriculture 33: 19-33.

Yao, Q., Chen, J., Guan, Z., Sun, C. and Zhu, Z., 2009. Inspection of rice appearance quality using machine vision. In: Intelligent Systems GCIS '09, WRI Global Congress on Intelligent Systems, May 19-21, 2009. Xiamen, China P.R., pp. 274-279.

Yun, Y.-T., Chung, C.-T., Lee, Y.-J., Na, H.-J., Lee, J.-C., Lee, D.-H., Lee, K.-W., Kang, J.-W. and Ahn, S.-N., 2015. Variation of yield and quality in early maturing rice cultivars by transplanting date in Chungnam plain area in Korea. Plant Breeding and Biotechnology 3: 47-57.

Zapotoczny, P., Zielinska, M. and Nita, Z., 2008. Application of image analysis for the varietal classification of barley: morphological features. Journal of Cereal Science 48: 104-110.

Zareiforoush, H., Minaei, S., Alizadeh, M.R. and Banakar, A., 2015. A hybrid intelligent approach based on computer vision and fuzzy logic for quality measurement of milled rice. Measurement 66: 26-34.

Zareiforoush, H., Minaei, S., Alizadeh, M.R. and Banakar, A., 2016a. Qualitative classification of milled rice grains using computer vision and metaheuristic techniques. Journal of Food Science and Technology 53: 118-131.

Zareiforoush, H., Minaei, S., Alizadeh, M.R., Banakar, A. and Samani, B.H., 2016b. Design, development and performance evaluation of an automatic control system for rice whitening machine based on computer vision and fuzzy logic. Computers and Electronics in Agriculture 124: 14-22.