Fissure Detection and Measurement in Rough Rice Using X-ray Imaging

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ABSTRACT. Fissures in rice kernels that develop prior to harvest and post-harvest processing significantly reduce head rice yield, a crucial parameter for evaluating rice quality and economic value in the rice industry. In this study, fissures in rough rice were revealed by scanning approximately 50 rough rice kernels at a time using an x-ray system. An algorithm was developed to detect and measure fissures in rough rice kernels in the x-ray images using the Python programming language coupled with the OpenCV library. This algorithm successfully segmented individual rice kernels in the x-ray images using the gap-filling method. The algorithm detected fissures by adaptive thresholding of each rice kernel and applying a series of filters. Data on kernel parameters (number, area, length, and width) and fissure parameters (percentage of kernels fissured and fissure number, area, and length per kernel) were produced for the images to characterize kernel size and fissuring levels of the rice sample. This algorithm demonstrated good repeatability in measuring kernel and fissure parameters, with relative standard deviations of less than 4% and 9%, respectively. The accuracy of the developed algorithm in measuring fissures was validated by visual inspection of rough rice, with a deviation of less than 2% in percentage of kernels fissured. The fissure detection and measurement algorithm provides a useful tool for quantifying fissures in rough rice samples using x-ray imaging. This information could be used to quantify fissuring levels and predict head rice yield for rough rice samples without a cumbersome milling process.

Keywords. Cracks, Fissure, Imaging, Rice, X-ray.

Rice is the staple food for at least half of the world’s population, providing up to 50% of the dietary caloric supply for people in Asia and Africa (Ngunyen, 2002). Global production of milled rice is approximately 480 million metric tons per year (Muthayya et al., 2014). Rice is mainly consumed as intact kernels; broken kernels have approximately half the economic value of intact kernels. Head rice yield (HRY) is defined as the ratio of the mass of head rice (milled rice kernels with a length ≥3/4 of the original kernel length) to the total mass of the rough rice sample. HRY is a crucial parameter when evaluating rice quality and market value (Siebenmorgen et al., 1992). The presence of fissures in a rice kernel renders the kernel susceptible to breakage during the milling process and results in HRY reduction. Thus, HRY is impacted by the percentage of fissured kernels in a rice sample (Jia et al., 2002; Odek et al., 2017a). Fissures form and develop in rice kernels through rapid moisture adsorption and intra-kernel material state gradients during the drying and tempering processes (Iguaz et al., 2006; Schluterman and Siebenmorgen, 2007). Formation of rice kernel fissures during drying and post-processing are impacted by various factors, including moisture content (MC), cultivar, air relative humidity, and temperature (Siebenmorgen et al., 2009; Odek et al., 2017b).

Minimizing kernel fissuring, and thereby minimizing HRY reduction, is a critical goal of the rice industry. Detection of fissure formation in rice kernels has been studied by a number of researchers. Fissures in brown and milled rice can be detected using laboratory instruments such as fissure inspection boxes (Cnossen et al., 2003; Iguaz et al., 2006; Bautista et al., 2009), video microscopes (Bautista et al., 2000), and grainscopes (Cao et al., 2004; Siebenmorgen et al., 2005). The most commonly used method for fissure detection is to scan the brown and milled rice using a CCD camera or a scanner to obtain rice fissure images for further image processing (Courtois et al., 2010; Jia et al., 2002; Lan et al., 2002; Lin et al., 2012; Shimizu et al., 2008). However, the visible light captured with a CCD camera cannot penetrate rice hulls, so this technique can only reveal surface fissures in brown or milled rice. For fissure detection in rough rice, an x-ray scanner can effectively penetrate the hull for internal fissure imaging and therefore has been applied by multiple investigators to detect fissures in rough rice (Kumar and Bal, 2007; Lakshmi et al., 2016).

Various methods have been applied for fissure detection to achieve better detection accuracy. Lakshmi et al. (2016) applied “canny” edge detection, a classic edge-detection algorithm method, to detect fissures. Lin et al. (2012) applied B-spline wavelets for fissure detection. This method can...
smooth the image while preserving and highlighting the fissure region. Xu and Li (2008) compared various methods (Sobel, Robert, Prewitt, Laplacian, and wavelet transform) for fissure detection. Results showed that the wavelet transform method performed better than the other methods in detecting internal fissures in milled rice kernels. The wavelet transform method classified rice kernels into groups of none, single, double, and multiple fissures with accuracies of 96%, 93%, 84%, and 83%, respectively. Courtois et al. (2010) classified milled rice kernels into non-fissured, soft-fissured, and hard-fissured kernels based on the number of subparts in milled rice kernels. The procedures used in these studies involved noise removal, gamma correction, image thresholding, and edge detection methods to detect, count, and classify fissures. However, the drawback of applying edge detection algorithms for fissure detection is that some critical geometric parameters of fissures, such as fissure length and fissure area, cannot be obtained. As such, no study was found that measured fissure geometric parameters. However, such parameters are important in analyzing fissure formation and development during rice processing, as well as in assessing the fissure level of rice samples. Thus, a new method for detecting and measuring rice fissures was deemed necessary to better characterize fissures in rough rice kernels. In this study, rice fissures were revealed by adaptive thresholding and applying a series of filters (area, grayscale, length, etc.). The parameters of the filtered fissures were measured to characterize the fissure levels of the rice sample.

Rice kernel segmentation, especially for touching kernels, is another important aspect that needs to be improved in image processing algorithms for greater efficiency and to make the algorithms more practical for application in the rice industry. In most previous studies on fissure detection in rice, the images contained only a single kernel (Jia et al., 2002; Lan et al., 2002; Lin et al., 2012; Xu and Li, 2008). In some studies with multiple kernels in the images, individual rice kernels were selected manually and segmented with cutting tools using image processing software, such as Adobe Photoshop, before applying fissure detection algorithms (Lakshmi et al., 2016; Kumar and Bal, 2007). Because typical rice kernels are elliptical in shape, classical watershed segmentation methods are not effective in segmenting touching kernels. The gap-filling method, which involves skeletonizing the background image and filling the gaps, was found to be highly effective for segmentation of touching rice kernels (Faessel and Courtois, 2011). The gap-filling method was successfully applied to segment approximately 200 milled rice kernels in images obtained with a flatted scanner (Courtois et al., 2010). In the present study, the gap-filling method was applied for effective segmentation of rice kernels, followed by a fissure detection and measurement algorithm.

Assessing fissures in rough rice kernels can provide a clear indication of internal fissure development in rough rice during drying and handling, as well as prediction of the HRY of specific samples. The goals of this study were to develop an image processing algorithm to automatically detect and measure fissures in rough rice kernels from x-ray images and then output the fissure parameters. To accomplish these goals, the following objectives were formulated:

1. Segment and select individual rough rice kernels in x-ray images.
2. Detect and measure fissures within individual rough rice kernels.
3. Output images with detected fissures and files documenting the kernel and fissure parameters for rice kernels.
4. Validate the repeatability and accuracy of the developed algorithm for fissure detection and measurement.

MATERIALS AND METHODS
RICE SAMPLE PREPARATION AND X-RAY IMAGING SYSTEM

Long-grain rice cultivar CL XL745 was used in this study to develop and validate the fissure detection and measurement algorithm. The rough rice samples were harvested from the University of Arkansas Northeast Research and Extension Center near Keiser, Arkansas, in 2018. The samples were harvested at 23.5% MC and were then naturally dried in ambient air to approximately 20% MC (high-MC lot), 18% MC (medium-MC lot), or 16% MC (low-MC lot). The three sample lots were dried in a chamber at 60°C with 20% relative humidity for 5, 10, 20, and 30 min. Following drying, the samples were then tempered at 60°C for 4 h. The difference in initial rice MC and drying time produced 12 rough rice samples (approx. 500 g of each sample) with varying fissuring levels (approx. 0% to 60% of the kernels fissured). Thus, these samples were used for validating the accuracy of the developed algorithm at varying fissuring levels. One sample lot that had approximately 40% of the kernels fissured (high-MC lot that was dried at 60°C for 20 min) was used to test the repeatability of the procedure as well as variability of the measured fissure parameters as impacted by the number of kernels scanned by x-ray imaging. For the repeatability test, 50 rough rice kernels were randomly selected and randomly spread on a plate for x-ray scanning. The 50 kernels were then recovered and re-spread on the plate for another x-ray scanning, for a total of ten repetitions. For the variability test with increasing numbers of rice kernels, 25, 50, 75, 100, 125, and 150 kernels were randomly selected, spread on a plate, and scanned by x-ray. Each plate contained at most 50 kernels; samples with more than 50 kernels were split among multiple plates. The variability test was conducted in triplicate. The variabilities of the fissure parameters were expressed by their relative standard deviations.

Rough rice kernels were scanned with an x-ray scanning system (UltraFocus 60, Faxitron Bioptics LLC, Tucson, Ariz.) for fissure detection. According to previous research (Odek et al., 2017a), a 3× magnification level was selected so that there were approximately 50 rough rice kernels in each x-ray image. The rough rice kernels were spread on the plate in a single layer for x-ray imaging. Some rice kernels may have been in contact but did not overlap each other. The fissures in the rice kernels were clearly detectable in the x-ray images by visual inspection at the 3× magnification level. Further details on the x-ray system and the imaging procedures are provided by Odek et al. (2017a).
The fissure detection and measurement algorithm was developed using the open-source language Python coupled with the OpenCV library. The image processing procedure for fissure detection and measurement is shown in figure 1. The first step was to segment individual rice kernels, and then the kernel parameters were measured. For each rice kernel, the fissures were segmented, and their parameters were measured. At the end, the program output an image plotted with fissures in color and a file that documented the kernel and fissure parameters.

Rice Kernel Segmentation and Measurement

Rough rice kernels consist of two major components: the hull and the caryopsis. The caryopsis comprises a starchy endosperm and a tightly adhered bran layer. In x-ray images, the hull is clearly distinguishable from the caryopsis (fig. 2). Approximately 50 rice kernels at a time were scanned with the x-ray system.

To segment individual rice kernels, the raw x-ray image was first blurred using Gaussian blurring with a kernel pixel size of 20. Image noise, fissures, and hulls were removed by the blurring process. Image thresholding was then performed using Otsu’s method (Otsu, 1979), and the x-ray image was converted to a binary image (fig. 3). There were several major defects in the binary images, including remains of header text, sterile lemmas, and touching rice kernels (fig. 3). The header text and sterile lemmas of rice needed to be removed. These unwanted objects had a smaller contour area compared to the rough rice kernels, which had a contour area between 2000 to 3500 pixels. Thus, the header text and sterile lemmas were filtered out by setting the minimal contour area of rice kernels to 1000 pixels. The contour area was calculated by applying the “findcontours” and “contourArea” functions in the OpenCV library. Rough rice kernels after filtering out the header text and sterile lemmas are shown in figure 4a, which still contains touching kernels.

Touching kernels were segmented using the gap-filling method, as described by Faessel and Courtois (2009). In summary, a skeleton of the background image was introduced to draw lines between touching kernels (fig. 4b). The open lines resulting from skeletonizing were then prolonged and propagated according the direction from their corresponding end points (fig. 4c). Finally, the touching rice kernels were split into individual kernels by the connected skeleton, and the segmented kernels were numbered, as shown in figure 4d. Following segmentation of the individual rice kernels, the parameters (kernel area, length, and width) of each kernel were measured. Kernel area was determined using the “contourArea” function in the OpenCV library. Kernel length and width were determined from the dimensions of a rotated bounding rectangle with minimal area (fig. 4d).

Fissure Detection, Segmentation, and Measurement

The procedure for fissure detection in individual rough rice kernels is shown in figure 5. For each selected rice kernel, fissures were first revealed using adaptive thresholding (Bradley and Roth, 2007). Compared to global thresholding, adaptive thresholding accommodates varying lighting conditions in the image and exposes fissures more fully in rice kernels. The kernel interiors were more clearly visible after adaptive thresholding (fig. 5). However, there were some noise, non-fissure contours, and outer boundaries of rice kernel that could interfere with fissure measurement and classification. The next step was to remove the boundaries of rice kernels and retain only the internal contours by erosion with a kernel pixel size of 3 and three iterations. After this process, interior fissures, noise, and non-fissure contours still remained. The irrelevant contours and noise were removed using an area filter (contours that had an area of less than 30 pixels were removed). As a result, only a few contours remained after passing through the area filter. Some of these contours were interior fissures; however, others were random contours and had a greater grayscale values than fissures.

Because the fissures inside rough rice kernels were of

Figure 1. Flowchart of image processing procedure for fissure detection and measurement in x-ray images.

Figure 2. X-ray image of rough rice kernels before image processing.

Figure 3. Binary image of rough rice kernels after Otsu thresholding.
lower grayscale value compared to the rest of the kernel area (typically less than 0.92 times the grayscale value of a rice kernel), interior non-fissure contours could be filtered out using a grayscale filter. Contours that had an average grayscale value greater than 0.95 times the average grayscale value of a rice kernel were not considered fissures and thus were filtered out. After grayscale filtering, multiple horizontal contours were removed. The final step was to remove some contours that closely resembled fissures in the rough rice kernels but were just natural indentations in the embryo region (i.e., the right bottom region of the kernel in fig. 5). These contours were filtered out with length and location filter. The method for measuring length and location are discussed in the following paragraph. Any contours with lengths less than 30 pixels and in the embryo region were filtered out by passing the binary images of the rough rice kernels through the length and location filters, leaving only fissures in the processed image. The fissure detection procedure was applied to each of the rough rice kernels, one by one, in the x-ray image.

Following fissure detection in the rice kernels, the next step was to measure the fissure parameters, including fissure length, width, area, and relative location. The procedure for fissure dimension measurement is shown in figure 6. The fissures inside individual rice kernels were selected and painted into a white canvas, and then the image was inverted to a black background. Fissure area on the canvas was measured using the “contourArea” function of the OpenCV library. Because fissures are of irregular shape and non-uniform width, it is impossible to measure their length and width directly. Instead, the average fissure length and width could be measured by skeletonizing each fissure to 1-pixel width. In this case, fissure length equals the area of the skeletonized

Figure 4. Rice kernel segmentation using gap-filling method: (a) binary image of rice kernels, (b) background image skeleton over rice kernels, (c) propagated background image skeleton, and (d) segmented and numbered rice kernels.

Figure 5. Procedure for fissure detection inside a rice kernel.
The average width of the original fissures was obtained by dividing the fissure area by the fissure length. The dimensions of the kernels and fissures measured by image processing were in pixels, which could be converted to millimeters by multiplying with a unit conversion ratio. The unit conversion ratio was obtained by dividing the length of a needle in pixels in the x-ray image to millimeters as measured with a caliper (Grainger, Inc., Lake Forest, Ill.).

Fissure location is the position of the center of the fissure’s bounding rectangle inside the rice kernel. The relative location of a fissure within an individual kernel was determined as its location relative to the center of the kernel (fig. 7). Fissure relative locations in the \( X \) and \( Y \) directions were calculated according to equation 1:

\[
X_r = \frac{x_1 - x_0}{a}, \quad X_r \in [-1, 1] \\
Y_r = \frac{y_1 - y_0}{b}, \quad Y_r \in [-1, 1]
\]

where \( x_0, y_0 \) are the coordinates of the center of the rice kernel, and \( a \) and \( b \) are half of the kernel’s length and width, respectively.

Output Image of Detected Fissures and Text File of Kernel and Fissure Parameters

The program developed in this study can run interactively to detect and measure fissures in rice kernels in an x-ray image. The procedure can be conducted on a single image or on an entire directory of images. For each processed x-ray image, an image was generated showing kernel index numbers and detected fissures (in colored lines) on the original image (fig. 8). In addition, for each processed x-ray image, a text file was produced as a summary of the kernel and fissure parameters including:

- Kernel parameters: number of rice kernels, mean kernel area, mean kernel length, and mean kernel width.
- Fissure parameters: percentage of kernels fissured, fissure area per kernel, fissure length per kernel, and number of fissures per kernel.

RESULTS AND DISCUSSION

REPEATABILITY OF KERNEL AND FISSURE PARAMETERS WITH ALGORITHM

The kernel and fissure parameters measured with the developed algorithm for ten repetitions of scanning one rice sample are presented in table 1. For all ten repetitions, all of the kernels were correctly segmented, demonstrating great effectiveness in segmenting rough rice kernels in x-ray ima-
ges when 50 rough rice kernels were spread on the plate. Kernel parameters were assessed with high repeatability using the developed algorithm. Repeated measurements of kernel area, length, and width were within less than 4% relative standard deviation (RSD). Compared to the kernel parameters, the fissure parameters were assessed with slightly higher variability, but still less than 10% RSD. The RSD values for the percentage of kernels fissured and the fissure number, area, and length per kernel were less than 7%, 9%, 6%, and 6%, respectively. These results demonstrate that the developed image processing algorithm is capable of assessing both kernel and fissure parameters with high repeatability (RSD < 10%). Because an x-ray image is a two-dimensional representation of the fissures, much of the variability in the repeated measurements using the developed algorithm was likely caused by the random positioning of the fissures when the kernels were randomly spread on the plate for x-ray scanning.

**VARIABILITY OF FISSURE PARAMETERS WITH INCREASING NUMBER OF RICE KERNELS**

Following validation of the repeatability of the developed algorithm, another question that needed to be answered was how large the subsample size (number of kernels) should be for x-ray scanning to adequately represent the fissuring level of a rough rice sample. The variability of the fissure parameters for triplicate subsamples with selected numbers of rice kernels should be within 10% RSD to satisfactorily represent the fissuring levels in the sample. The change in the relative standard deviation of the fissure parameters with an increasing number of rough rice kernels is plotted in figure 9. As expected, the RSD of all fissure parameters decreased with an increasing number of rice kernels scanned by the x-ray system. Among the four fissure parameters evaluated, the percentage of kernels fissured had the least RSD and is thus considered the best fissure parameter for estimating fissuring levels in rough rice samples using x-ray scanning and processing with the developed algorithm. When the number of rough rice kernels was increased to 125, the RSD values of all fissure parameters were reduced to less than 10%. Thus, it is advisable to randomly select a sample of at least 125 rough rice kernels for assessing the fissuring level with x-ray imaging. Further increase in the number of rough rice kernels scanned by the x-ray system to more than 150 kernels could further reduce the RSD of the fissure parameters, resulting in a better representation of the fissuring level in a rough rice sample.

**ACCURACY OF FISSURE PARAMETERS WITH DEVELOPED ALGORITHM**

To validate the accuracy of developed algorithm for measuring fissure parameters, fissuring levels for twelve rough rice samples (approx. 0% to 60% kernels fissured) were evaluated using the developed algorithm. Among the four fissure parameters, the percentage of kernels fissured and the number of fissures per kernel could be determined by visual inspection. These two fissure parameters were evaluated using image analysis with the developed algorithm and are plotted against the results from visual inspection in figure 10. Both fissure parameters (percentage of kernels fissured and number of fissures per kernel), as measured with the developed algorithm, correlated highly with the results obtained from visual inspection, with correlation coefficients (R²) of 0.998 and 0.997, respectively. For samples with percentages of kernels fissured ranging from 0% to 60%, the largest deviations in the percentage of kernels fissured and in the number of fissures per kernel as measured with the developed algorithm and visual inspection were less than 2% and 0.08, respectively. These results affirm that the developed algorithm matched human visual inspection for detection and measurement of fissures in rough rice kernels in x-ray images.
CONCLUSIONS

An image processing algorithm was developed to detect and measure fissures in x-ray images of approximately 50 rough rice kernels. The algorithm automatically segmented touching kernels using the gap-filling method and then detected and measured rice fissures in individual kernels. The algorithm demonstrated good repeatability in measuring kernel and fissure parameters, with relative standard deviations of less than 4% and 9%, respectively. A sub-sample of at least 125 randomly selected kernels is recommended to represent the fissuring level of a respective rough rice sample. The accuracy of the developed algorithm was validated by comparison with visual inspection, with a deviation of less than 2% in the percentage of kernels fissured. This study provides a useful tool to detect and measure fissures in images of rough rice kernels from an x-ray scanner. The fissure detection algorithm could be applied to predict head rice yield and possibly be extended to detect internal damage in other crops and grains.

ACKNOWLEDGEMENTS

The authors acknowledge the financial support provided by the corporate sponsors of the University of Arkansas Rice Processing Program and the Arkansas Rice Research and Promotion Board. The authors are grateful for the review and suggestions from Bhagwati Prakash, a postdoctoral research associate in the rice processing program at the University of Arkansas.

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