An Improved Algorithm for Fourier series Approximation Based Algorithm for Separating Touching Grain Kernels

S. B. Ghadge , Dr. S. D. Raut

Abstract- A proposed algorithm is using elliptic Fourier series approximation for separating touching grain kernels. Algorithm is based on boundary curvature values. The image acquisition inefficiency can be removed by using image pre-processing techniques and Fourier approximation smoothes the boundary contour which avoids the local pseudo-corners of kernel caused by the presence of rough boundaries. Nodal points separating the touching instances are determined after calculating curvature values along the boundary of kernels. Final nodal points are determined by evaluating the curvature along the boundary of image and selecting those which falls below threshold. With multiple nodal points, the segmentations lines are drawn using nearest-neighbor and critical radian distance difference [rad] of chain coded boundary point. The algorithm uses Breshenham algorithm for drawing segmentation lines. The algorithm appears to be robust enough to separate most of the multiple touching scenarios.

Index Terms- Fourier Series, Grain separation, Curvature analysis, nearest neighbour

I. INTRODUCTION

For millennia, the grains humans ate came straight from the stalk. That means they got a carbohydrate package rich in fiber, healthy fats, vitamins, minerals, plant enzymes, hormones. So determining grain type and quality is of great importance. Despite technological advances in the transportation and handling of grain, the analysis of quality attributes and grading of grain is still performed manually by skilled personnel (Lou, Jayas, & Symons, 1999). Manual analysis of grains is prone to many problems: (i) it is highly immanent and is affected by human factors and working conditions (Zhang, Jayas, & White, 2005); (ii) the rate of cleaning and recovery of salvages is limited; and (iii) human sense can easily be influenced by external factors (Francis, 1980) resulting in grading inconsistencies .

In this respect a machine vision system is needed for monitoring and handling grain operations. Machine vision is nothing but to extract useful information from digital images automatically. It implies that a system is needed to automatically cleaning and separation of grains which will be able to apply evaluation criteria consistently and objectively and without any tiredness.

Machine Vision systems are widely in use for applications like inspection of fruits (Shahin & Symons, 2003), vegetables (Schatzki et al., 1997) and grains (Liao, Paulsen, & Reid, 1994). Classification of grains like of wheat and barley using Machine vision (F. Guevara-Hernandez and J. Gomez-Gil). Also by classification based on measurements of morphological, optical and textural features of various grain types (Samir Majumdar, 1997), (A. Douik, M. Abdellaoui, 2010), and for particular grains types such as wheat (Neuman, Sapirstein, Shwedyk, & Bushuk, 1987; Paliwal, Shashidhar, & Jayas, 1999, 2003), rice (Yao, Chen, & Guan, 2009,274e279 p.), corn (Paulsen, Wigger, Litchfied, & Sinclair, 1989), lentils (Shahin & Symons, 2003), and paddy (S. F. Lilhare, N G Bawane, 2012) has been reported. A number of studies have been conducted to classify grains based on their physical attributes (Paliwal et al., 2003, 1999).

Most of the previous feature extraction algorithms have been applied to grain kernel images that were presented to the imaging systems manually in a non-touching fashion. This is to avoid clusters of touching kernels that make the feature extraction procedure difficult. Despite the use of vibrating beds to present grain kernels in a monolayer, the presence of touching scenarios cannot be avoided (Crowe, Luo, Jayas, & Bulley, 1997). A study using a sample presentation system consisting of a vibratory feeder and a conveyor belt showed that about 90% of the kernels were presented as individual kernels (Crowe et al., 1997). Most of the touching grains were in groups of two whereas multiple touching kernels (a group of three or four) represented less than 4% of the total grains presented (Crowe et al., 1997).Zhang et al. (2005) demonstrated that the focus of algorithm development should be on separating two and three touching scenarios since multiple touching conditions can be eliminated using mechanical systems. Combining such a grain presentation device and using machine vision will, however, add extra cost to the development of the overall system. Different methods of separating touching kernels have been reported in literature. Automated separation of touching grains in digital images of thin sections by E.H. van den Berg, A.G.C.A. Meesters, J.A.M. Kenter, W. Schlager (2000). The new algorithm for separation detects the characteristic sharp wedges when grain sections touch and evaluates them for possible starting points of separation lines.

These include the use of morphological operations (Shatadal, Jayas, & Bulley, 1995), an ellipse-fitting algorithm (Zhang et al., 2005), a concavities based algorithm (Visen, Shashidhar, Paliwal, & Jayas, 2001), watershed segmentation (Wang & Paliwal, 2006) and a combined watershed and concavity algorithm (Zhong et al., 2009). However, these algorithms had certain drawbacks: (i) the morphological operations failed to correctly segment when groups of touching kernels formed relatively longer chains; (ii) the concavity algorithm was prone to oscillations and was only successful to separate a maximum of three touching kernels (Visen et al., 2001); (iii) the ellipse-fitting algorithm proposed by Zhang et al. (2005) was restricted to two touching kernel scenarios and its search for fitting ellipses was

time consuming; (iv) the watershed algorithm was prone to over segmentation and failed to segment elongated grains despite significant improvements by reconstructing internal markers through a series of morphological operations (Wang & Paliwal, 2006); and (v) the procedure which combined watershed and concavities algorithms was very lengthy. Hence, comprehensive and robust touching grain segmentation algorithms are still lacking. In this respect, an efficient separation algorithm based on the elliptic Fourier series approximation and the calculation of curvature values is proposed. The Fourier approximation ensures perfect smoothness such that all derivatives exist and are continuous. The corner locations are determined at points where abrupt changes in the local curvature value are detected. In an ideal situation, when the touching objects have smooth boundaries, all negative curvature values define corner points. However, if the kernels are broken or have rough boundaries, pseudo corner points may be detected. To avoid such pseudo corner points, a threshold curvature value has to be defined. In this study, a threshold value (.28, .3) avoided the surface roughness effects. The objective of this research, therefore, is to develop an algorithm that separates multiple touching grains kernels.

II. RESEARCH ELABORATION

2.1. Imaging and image processing:

Images are taken from Rapid-I machine under fluorescent light of 36 watts, of dimensions 800×600, width 800 pixels, height 600 pixels, horizontal resolution 96 dpi, vertical resolution 96 dpi, at bit depth of 24.

2.2. Grain samples:

The grain samples were obtained from wheat available in the market. Available sample is of type Gujarati No. 1. The wheat grains were manually placed in clusters of two, and three, and four grains. The pictures are taken after manually placing them in touching fashion.

2.3. Image pre-processing:

The sample image taken might have noise because of processing such image can be difficult and may not give desired output. So, image pre-processing techniques are applied for the same. First the RGB image is converted to HSV image. Output image is converted to binary image for easy processing depending upon the threshold. Boundaries are cleared. The image processing and boundary tracing is done in Matlab R2009b.
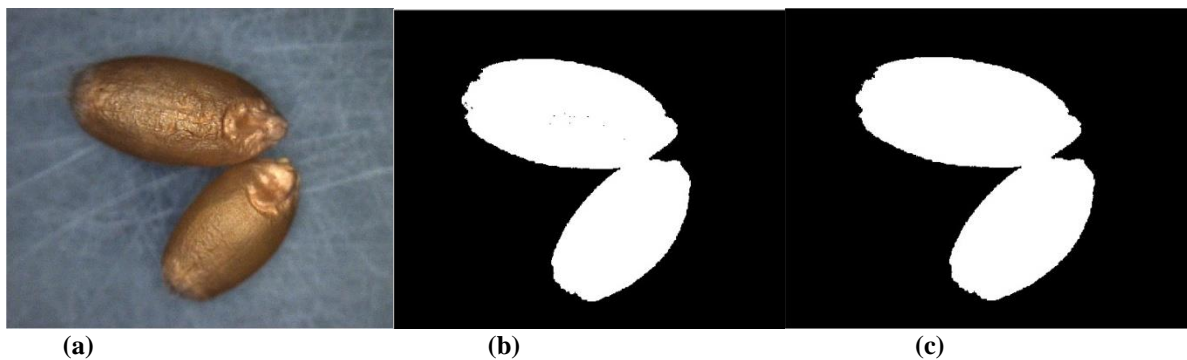

(a)   **(b)**   **(c)**

Fig 1. (a) Input image with 2 wheat grains (b) Binary image of input image (c) Pre-processed image from binary image.

2.4. Elliptic Fourier series approximation:

The Fourier approximation ensures perfect smoothness such that all derivatives exist and are continuous. Fourier descriptors refers to the utilization of Fourier analysis, primarily the Fourier series as a curve fitting technique, that can numerically describe the shape of irregular structures such as are commonly found in living organisms. The quantitative characterization of irregular forms is often the first step toward elucidation of the underlying biological processes, whether they are genetic, evolutionary, or functional. The elliptical Fourier method is primarily an analytical means to represent a curve as a function, and it makes use of geometry of a form only indirectly via approximation of the overall shape as an ellipse used to orient the representation, which then allows for a rotation, translocation, and redefinition of the initial point to remove coordinate-system dependency. Fourier approximation is represented as equation in of (x, y) point in the form of third variable (t). Based on discrete Fourier series approximation Fourier coefficients are calculated for chain-coded boundary contours. Chain code of is started from a pixel as a reference point and chain code completes when the reference point is reached (Mebatsion and Paliwal, 2011). The elliptic Fourier series approximation of closed contour projected

on the x and y-axis can be defined as follows (Hiraoka & Kuramoto, 2004; Neto, Meyer, Jones, & Samal, 2006):

$$x_N(t) = A_0 + \sum_{n=1}^{N} a_n \cos\left(\frac{2n\pi t}{T}\right) + b_n \sin\left(\frac{2n\pi t}{T}\right)$$

(1)

$$y_N(t) = C_0 + \sum_{n=1}^{N} a_n \cos\left(\frac{2n\pi t}{T}\right) + d_n \sin\left(\frac{2n\pi t}{T}\right)$$

t is the step required to move a unit pixel along the closed contour, such that $t_{p\_1} < t < t_p$ for values of p within the range of $1 \leq p \leq K$. N is the number of Fourier harmonics and K is the total number of chain-coded points. A_0 and C_0 are coefficients corresponding to the frequency 0. If the contour between the (i-1)[th] and the ith chain-coded points is linearly interpolated and the length of the contour from the starting point to the pth point and the perimeter of the contour are denoted t_p and T, respectively, then

$$t_p = \sum_{i=1}^{p} \Delta t_i$$

(2)

T is the basic period of the chain code, which is the overall step to traverse the entire contour, $T = t_k$, where Δt_i is the distance between the (i-1) th and the ith points. The Kth point is equivalent to the starting point. If the x-coordinate of the pth point is denoted by x_p, then,

$$x_p = \sum_{i=1}^{p} \Delta x_i, \qquad \text{and}$$

$$y_p = \sum_{i=1}^{p} y,$$

$$\text{(3)}$$

where Δx_i and Δy_i are the distances along the x and y axes between (i-1) th and the ith point. Assuming linear interpolation between the neighbouring points, the elliptic Fourier coefficients in Eq. (1) of the nth harmonic (a_n; b_n; c_n and d_n) can be calculated using the following equations (Hiraoka & Kuramoto, 2004; Iwata, Niikura, Matsuura, Takano, & Ukai, 1998; Neto et al., 2006):

$$a_n = \frac{T}{2n^2\pi^2} \sum_{p=1}^{K} \frac{\Delta x_p}{\Delta t_p} \left(cos\left(\frac{2n\pi t_p}{T}\right) - cos\left(\frac{2n\pi t_{p-1}}{T}\right) \right)$$

$$b_n = \frac{T}{2n^2\pi^2} \sum_{p=1}^{K} \frac{\Delta x_p}{\Delta t_p} \left(sin\left(\frac{2n\pi t_p}{T}\right) - sin\left(\frac{2n\pi t_{p-1}}{T}\right) \right)$$

$$\text{(4a)}$$

$$c_n = \frac{T}{2n^2\pi^2} \sum_{p=1}^{K} \frac{\Delta y_p}{\Delta t_p} \left(cos\left(\frac{2n\pi t_p}{T}\right) - cos\left(\frac{2n\pi t_{p-1}}{T}\right) \right)$$

$$d_n = \frac{T}{2n^2\pi^2} \sum_{p=1}^{K} \frac{\Delta y_p}{\Delta t_p} \left(sin\left(\frac{2n\pi t_p}{T}\right) - sin\left(\frac{2n\pi t_{p-1}}{T}\right) \right)$$

$$\text{(4b)}$$

The number of harmonics required is estimated from average Fourier power spectrum. The Fourier power of a harmonic is proportional to the amplitude and provides a measure of the amount of shape information described by that harmonic. For the nth harmonic, the Fourier power is computed by the following equation (Costa et al., 2009):

$$Fourier\ power = \frac{\sum_{n=1}^{N}(a_n^2 + b_n^2 + c_n^2 + d_n^2)}{2}$$

$$\text{(5)}$$

In this case, the Fourier harmonics were truncated at the value N, at which the average cumulative power was 99.99% or more of the total average power, calculated with N_{max}, equal to half the number of boundary points.

2.5. Corner detection by analyzing the curvature:

Corner points are important features of an object for computer vision. Because corner points give more information about object and are descriptive primitives for shape representation and image interpretation (Asada & Brady, 1986). A corner can be defined as a point for which there are two dominant and different edge directions in a local neighbourhood of the point. Corner points have been defined in many ways by different researchers such as, local maxima (Abe et al., 1993), the point with largest "cornerity index" (Guru, Dinesh, & Nagabhushan, 2004), the point with k-cosine value (Rosenfeld & Johnston, 1973; Sun, 2008), and the point with maximum change of curvature (Freeman & Davis, 1977). However, corner points are not simply local maxima, high curvature or dominant points. They are points which change the features of shape. The detection of a corner is a function of the magnitude of the discontinuity, its abruptness, and the curved regions either side of it over where the mean curvature can be considered to be uniform and free of discontinuities (Masood & Sarfraz, 2007). The absolute value of the curvature is a measure of how sharply the curve bends. Curves that bend slowly, which are almost straight, will have small absolute curvature. The curvature function K(t) is the derivative of the orientation function $\emptyset(t)$, expressed as (Frette, zirnovsky, & Silin, 2009; Walton & Meek, 2001):

$$\emptyset(t) = tan\left(\frac{dy(t)}{dx(t)}\right), k(t) = \frac{dx(t)d^2y(t) - d^2x(t)dy(t)}{(dx(t)^2 + dy(t)^2)^{\frac{3}{2}}}$$

$$\text{(6)}$$

where k(t) is the curvature, $dx(t)$, $dy(t)$ and $d^2x(t)$, $d^2y(t)$ are the first and the second derivatives of x and y with respect to t, respectively. Most healthy grains are generally convex and when convex objects are in contact, they form concave contour regions where the local curvature values are negative. Nodal points for multiple touching objects are determined from curvature values that fall below a certain threshold value (Freeman & Davis, 1977; Mebatsion and Paliwal, 2011).

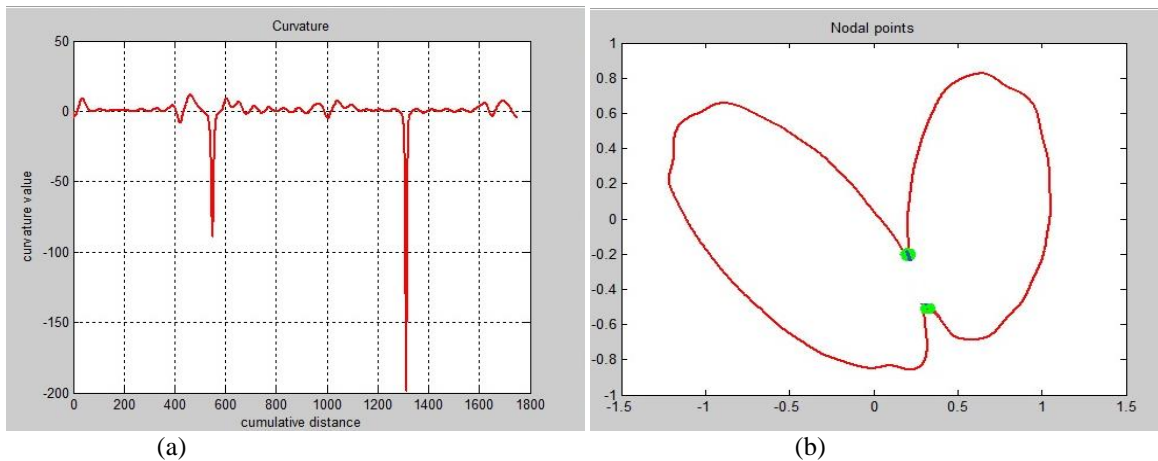(a)   (b)

Fig.2 (a) The curvature value as a function of cumulative radial distance of multiple touching grains presented in Fig. 1. The corner points are quite easily identified having curvature values significantly different from that of the rest of the boundary points of the touching grain kernels. The critical curvature value of -50. (b) The nodal points (marked with green spot) used for separating multiple touching grains. The corresponding curvature value of the nodal point is presented in Fig. 2.

Fig. 2 (a) shows the curvature value as a function of cumulative distance of multiple touching grains. Based on the curvature values, the nodal points can accurately be defined on the elliptic Fourier series approximation curve depicted in Fig. 2 (b)
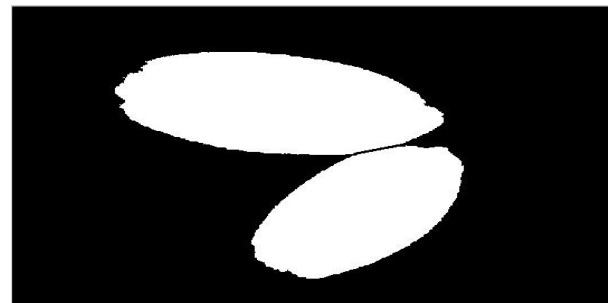
2.6. Determination of segmentation lines:

For determining segmentation lines Euclidian distance between each pair of points is calculated and arranged in ascending order. For joining pair *nearest-neighbour* algorithm is used. The first pair was taken to define the first segmentation line. The list of pairs was then automatically edited to remove any other pair containing any of the pixels forming the first pair. Subsequent segmentation lines were determined by repeating the procedure until all the node pairs were exhausted (Mebatsion and Paliwal, 2011; Visen et al., 2001). Nearest-neighbour criterion fails to separate touching grains where grains are slender in shape and have roughness (Mebatsion and Paliwal, 2011). This calls for the need to set additional requirements for the segmentation algorithm to be executed prior to the nearest-neighbour criterion. In this respect, a new algorithm that combines the nearest-neighbour algorithm and a radian critical distance difference is given by Paliwal (2010). The radial critical distance, L_s, is defined as the ratio of the radian measure of the perimeter of an elliptic Fourier approximation of a curve (the boundary of touching objects in this case) $(=2\pi)$ and the total number of potential nodes, n, defined as, $L_s = (2\pi/n)^{2/3}$. A one-pixel

(b) The nodal points (marked with green spot) used for separating multiple touching grains. The corresponding curvature value of the nodal point is presented in Fig. 2(a).

Fig. 3 Touching Grains with boundaries segmented.

thick flexible moving window (W_m) of length (L_s) is traced over a sub-segment from a "reference" node to the others. At each step the presence of a node point inside the moving window is examined. (H.K. Mebatsion*, J. Paliwal ; 2010). A list of "potential" node pairs is constructed from the reference node point and node points outside W_m; i.e., a node point inside W_m is ignored from being a potential node pair. The procedure is repeated for all node points. From the list of potential node pairs, the "true" node pairs are determined using nearest-neighbour criterion.
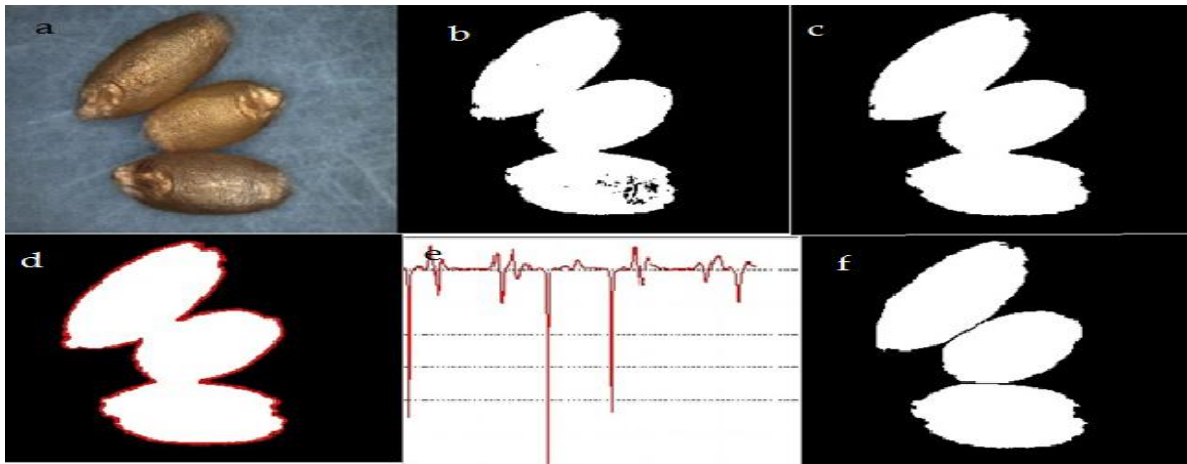
Fig. 4 A typical multiple kernel separation procedure for three grains: (a) original image showing multiple touching kernels; (b) Binary image (c) Pre-processed image (d) Fourier series approximation (red contours) of the boundary contours of touching kernels; (e) the curvature value as a function of cumulative radial distance where the nodal points are clearly identified; (f) separated kernels.
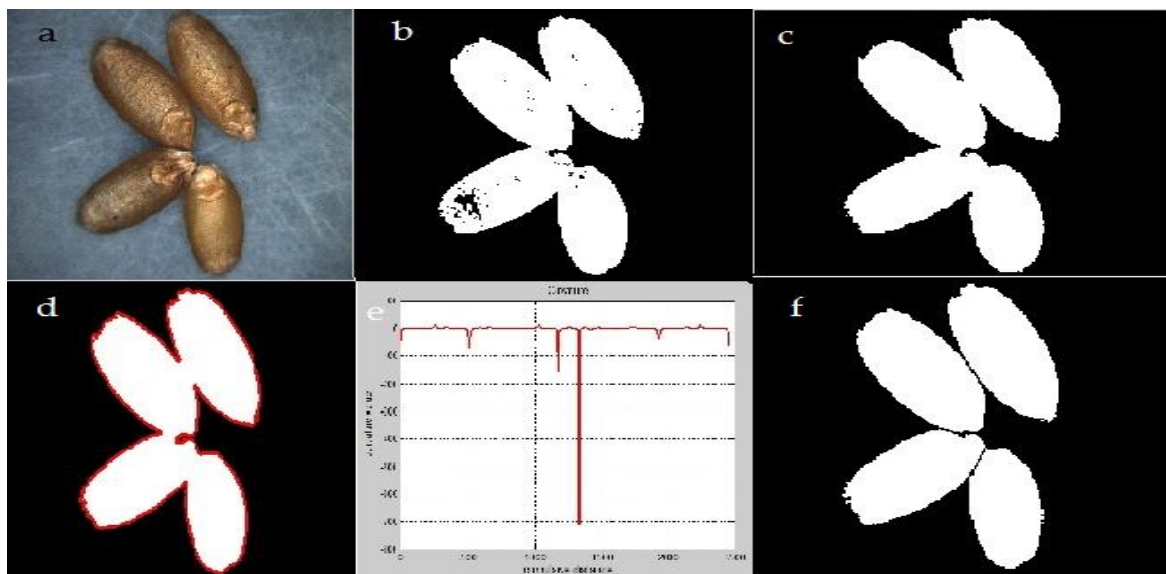

Fig. 5 A typical multiple kernel separation procedure for four grains: (a) original image showing multiple touching kernels; (b) Binary image (c) Pre-processed image (d) Fourier series approximation (red contours) of the boundary contours of touching kernels; (e) the curvature value as a function of cumulative radial distance where the nodal points are clearly identified; (f) separated kernels.

III. RESULTS

The proposed algorithm is able to separate most of the instances of multiple touching wheat grains irrespective of their orientation. The Figs. 4 and 5 show the steps of separating multiple touching grain kernels. Because of rough shape of grains separation algorithms fail to separate the grain properly. But Fourier series approximation overcomes this limitation and algorithm able to separate kernels properly.

IV. CONCLUSION

An elliptic Fourier approximation based segmentation technique to separate various scenarios of touching kernels for multiple grains was implemented. The algorithm successfully separated most instances of touching kernels. Fourier approximation helps to smoothen the rough boundaries of grain kernels and separate the contours correctly.

AUTHORS

First Author – S. B. Ghadge
Second Author – Dr. S. D. Raut