Processing of digital images of touching kernels by ellipse fitting

N.S. SHASHIDHAR, D.S. JAYAS, T.G. CROWE and N.R. BULLEY

Department of Biosystems Engineering, 438 Engineering Building, University of Manitoba, Winnipeg, MB, Canada R3T 5V6.
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Shashidhar, N.S., Jayas, D.S., Crowe, T.G. and Bulley, N.R. 1997. **Processing of digital images of touching kernels by ellipse fitting.** Can. Agric. Eng. **39**:139-142. An algorithm was developed to fit ellipses to digital images of separated and touching kernels with random orientations. The algorithm was evaluated for its ability to count objects in the images and to estimate length, width, perimeter, and area of individual objects. The estimated parameters were compared with the parameters determined using conventional image processing techniques on images of physically-separated kernels. All 300 kernels were counted correctly. In some situations, it may be possible that kernels would align in such a manner that they would not be separated and counted correctly by the algorithm. The estimated size features were not significantly different from the conventionally-determined parameters at p >0.05. Keywords: machine vision, grain identification, ellipse fitting, occluding objects, separation, feature extraction.

Un algorithme a été développé pour établir corrélation entre des ellipses et des images digitales de grains séparés et se touchant, disposés au hasard. L'algorithme a été évalué pour son aptitude à compter les objets compris dans les images et à estimer longueur, largeur, périmètre, et aire de chacun des objets. Les paramètres estimés ont été comparés avec ceux déterminés en utilisant les techniques conventionnelles de traitement d'image de grains physiquement séparés. Tous les 300 grains ont été comptés correctement. Dans certains cas, il peut être possible que les grains soient alignés de manière à ce qu'ils ne soient pas séparés et comptés correctement par l'algorithme. Les paramètres estimés des dimensions n'étaient différents de ceux déterminés avec la méthode conventionnelle qu'à p >0.05. Mots clés: vision machine, identification de grain, corrélation avec ellipse, reconnaissance d'objets, séparation, caractéristique d'extraction.

INTRODUCTION

Machine-vision systems have the potential of being used in the grain industry for identification and classification of different grain types and foreign materials in an inspection sample. An efficient machine-vision system can reduce sample-processing and inspection times and can eliminate the subjective aspects of grain quality evaluation. Traditionally, the input data for a machine vision system have come from a camera which acquires images of grain samples placed manually as individual kernels in the field of view of the camera. To implement the machine vision system in an industrial setting, it is necessary to present samples automatically and continuously. Samples placed randomly in a single layer on a moving belt may result in images with kernels touching and overlapping with their neighbours. Dropping a representative sample on a flat surface also gives touching and overlapping kernels.

Algorithms which can identify kernels in binary images of isolated grain kernels with 95% accuracy already exist (e.g. Sapirstein et al. 1987). However, these algorithms cannot identify the individual components in a group of touching kernels because the touching kernels are interpreted as individual objects which do not correspond to any instance of known kernels.

This problem of recognizing objects under partial occlusion is discussed in several papers in the area of pattern recognition. The techniques described in the literature are based on concepts such as contour matching (Chien and Aggarwal 1989), complex-log conformal mapping (Wechsler and Zimmerman 1988), invariants (Reiss 1993; Bruckstein et al. 1993; Rivlin and Weiss 1995), template matching (Ullmann 1992), Markov models (He and Kundu 1991), mathematical morphology (Shatadal et al.1995), and property based learning (Cho and Dunn 1994).

The algorithm reported in this paper departs significantly from the approaches reported in the published literature. The objective of this research was to develop an algorithm which can count the number of objects in a digital image and extract morphological features from images which include isolated and touching kernels without a need for physical separation of kernels.

ALGORITHM DEVELOPMENT

Fitting ellipses to grain kernels

The kernels were approximated as ellipsoids of revolution and it was assumed each kernel could be identified by the dimensions of its approximating ellipsoid. Or equivalently (in two dimensions), the identification could be done by determining the ellipse which "covers" the silhouette of the grain kernel and by comparing the dimensions of the ellipse with typical dimensions for a variety of grain types.

To find an ellipse which fits over an isolated grain kernel, the following simple scheme was proposed. The boundary of the kernel (Fig. 1) was determined by a simple boundary extraction program and was sampled randomly to yield five points labelled (x_1, y_1), (x_2, y_2), (x_3, y_3), (x_4, y_4), and (x_5, y_5). By successively substituting these points into a second degree equation (Eq. 1), five linear equations were obtained:

$$c_0 + c_x x + c_y y + c_{xy} xy + c_{xx} x^2 + c_{yy} y^2 = 1 \qquad (1)$$

which were solved to give the coefficients c_0, c_x, c_y, c_{xy}, c_{xx}, and c_{yy}. Equation 1 along with its coefficients was matched

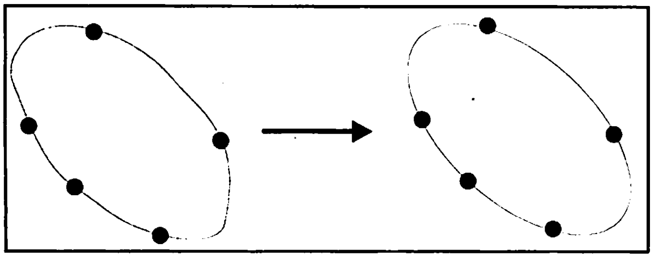

Fig. 1. Boundary sampling and ellipse fitting for shape approximation.

with the standard form of an ellipse (Eq. 2) to determine the parameters of the ellipse:

$$\left(\frac{(x - l_x)\cos\theta + (y - l_y)\sin\theta}{a}\right)^2 + \left(\frac{(-x - l_x)\sin\theta + (y - l_y)\cos\theta}{b}\right)^2 = 1 \qquad (2)$$

where:

(l_x, l_y) = centre of the ellipse,

a = semi-major axis,

b = semi-minor axis, and

θ = orientation of the major axis from the x-axis.

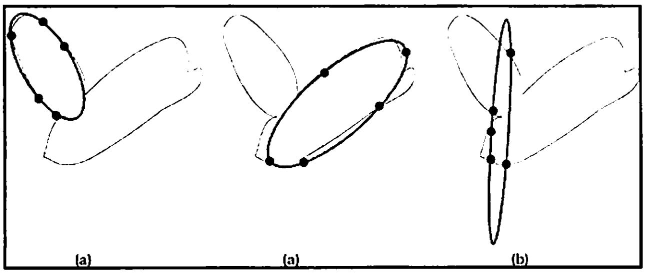

Fig. 2. Instances of correct (a) and incorrect (b) point selection for ellipse fitting.

Equation 2 was derived by applying translation and rotation transformations to the equation of the standard ellipse.

For images containing touching kernels, we used the following heuristic procedure for selecting the five points needed for ellipse fitting:

1) select a point randomly within a group of touching kernels,
2) radiate five lines randomly from the point, and
3) choose the intersections of the rays with the boundary as the five points through which the ellipse is to pass (Fig. 3). (No boundary extraction is needed to determine the point of intersection of a ray with the boundary because the change in the gray level can be used to stop the ray).

This procedure increased the probability of selecting all the five points on the partial boundary of the same kernel.

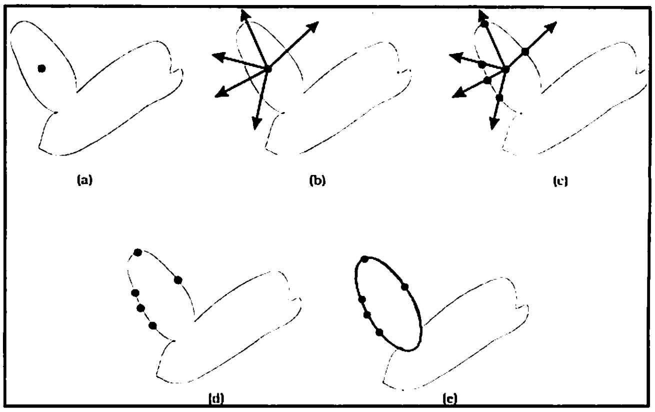

Fig. 3. Procedure for random point selection included: (a) define an interior point, (b) establish five random rays from the interior point, (c and d) identify points of intersection between rays and object boundary, and (e) fit an ellipse through the 5 selected points.

Cluster formation

If the grain kernels were perfect ellipses, each kernel would be matched with the same ellipse for every trial of the ellipse fitting procedure as long as the five points chosen were on the boundary of that kernel. Real grain kernels, however, are not perfect ellipses. If ellipses were fitted repeatedly to a particular grain kernel, a collection of similar ellipses is generated. The similarity among ellipses depends on how closely the grain kernel can be approximated by an ellipse. An example of clusters of fitted ellipses are shown in Fig. 4 along with the original kernel outlines. The clusters of ellipses in Fig. 4 were generated by invoking the ellipse-fitting procedure 80 times (for an image containing 25 touching or non-touching kernels, the algorithm was invoked 1000 times). From each cluster of ellipses, a representative ellipse was found as follows.

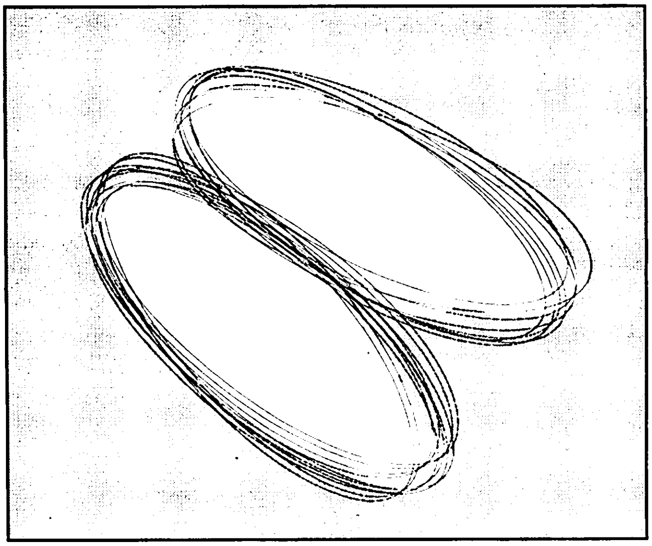

Fig. 4. Two grain kernels and the clusters of ellipses obtained by repeated ellipse fitting.

Reducing clusters to extract representative ellipses

After executing the algorithm on a group of touching kernels, let us refer to the set of all generated ellipses as $E = \{e_1, e_2, e_3, ...e_N\}$. As a first step in the reduction, let us eliminate from E all ellipses which have few neighbours. These were ellipses that occurred due to inappropriate point selection, as in Fig. 2. To do this, we first identified each ellipse as a point in the Euclidean space $\mathbf{R}^5$. Each point in $\mathbf{R}^5$ was defined by values of I_x, I_y, a, b, and θ. The distance between two ellipses was defined as the usual Euclidean distance, d, between the two corresponding points in $\mathbf{R}^5$. Two ellipses, e_i and e_j, were regarded as neighbours, if $d(e_i, e_j) < \delta$. For each ellipse, $e \leftrightarrow$E, we can associate an integer $N_\delta{}^E(e)$ which denotes the number of neighbours e has. So, we can extract the following subset E_r from E:

$$E_r = \{e : e \in \mathrm{E} \text{ and } N_\delta{}^E(e) > L\} \quad (3)$$

The real number, δ, and the integer, L, are design parameters and were determined through numerical trials. (When I_x, I_y, a, and b were in pixels, δ was 5 and L was 10). If δ and L are appropriately chosen, E_r contains well defined clusters of ellipses. Let us rename the elements of E_r such that we can write $E_r = \{e_1, e_2, e_3,...e_M\}$.

The next step is to isolate clusters in E_r and assign a representative ellipse to each cluster. Conceptually, the procedure to do this is stated as follows. Assume that a partial collection of clusters has been determined. Introducing a "new" ellipse into the cluster system will either cause some of the clusters (which happen to contain neighbours of the "new" ellipse) to coalesce and absorb the "new" ellipse or will result in the creation of a new singleton cluster containing just the "new" ellipse (if no such neighbours exist). The collection of clusters is modified every time a "new" ellipse is added. Effectively, the set of clusters is built up using ellipses picked out one at a time from E_r.

Sample preparation and image acquisition

Colour images for wheat, barley, oats, and rye were acquired with the imaging hardware described in Luo et al. (1996) which uses a circular fluorescent lamp with a light controller for illumination. The colour image contained red, green, and blue signals. For each grain type, 75 whole kernels were randomly selected from bulk commercial samples of grade 1 grains and divided into groups of 25 kernels. The 25 kernels were dropped onto a black background (100 mm x 100 mm) resulting in touching and non-touching kernels and an image was acquired. The touching kernels were physically separated such that the orientation of each kernel was not changed significantly (as far as manual handling allows) and the second image was acquired. The 12 images of touching kernels (4 grain types x 3 images per grain) were used as input to the ellipse fitting algorithm and the 12 physically-separated images were analyzed as follows to extract length, width, area, and perimeter for each kernel.

Feature extraction

The data from the red band were used for both types of images (touching and non-touching kernels) for feature extraction and ellipse fitting procedures. The data from other

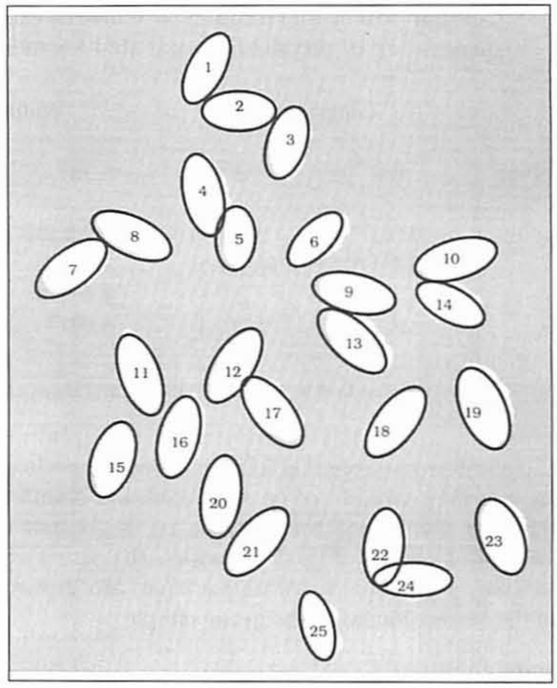

Fig. 5. The result from running the ellipse fitting algorithm on an image of wheat kernels.

two colour bands could have just as easily been used for obtaining binary images which were used for testing our algorithm. Prior to extracting features or fitting ellipses, the red band of all images was first transformed from rectangular pixels (spatial resolution of 0.206H x 0.161V mm) to square pixels with pixel sides measuring 0.197 mm. After the spatial transformation, silhouettes of grain kernels were separated from the black background by an automatic iterative thresholding operation. The thresholding operation selected an optimal threshold value and generated a binary image by assigning a value of zero (black) to all pixels which were below the threshold and a value of 255 (white) to pixels above the threshold.

After thresholding, the conventional feature extraction procedures (Nair 1997) began by labelling each blob in the binary image of separated kernels with a unique number. Small distinct blobs were ignored, while small holes in the silhouettes of kernels caused by the thresholding operation were filled. First, kernel areas were determined by counting the contiguous pixels of each entity and multiplying by the area of a single pixel, 0.0388 mm^2. After determining the 4-neighbour boundary of each kernel, perimeters were calculated by summing the Euclidean distances between successive pixels around the periphery. Finally, the length and width of each kernel were evaluated by determining the side lengths of a bounding rectangle oriented with one pair of opposite sides parallel to the major axis.

RESULTS

Object counting

Three hundred separated and touching kernels (3 images of 25 kernel each for 4 grain types) were presented to the ellipse fitting algorithm and were counted correctly. In some situ-

Table I: Comparison of morphological features extracted using the ellipse fitting algorithm (FE) and the image processing of physically separated kernels (AS)

	Length (mm)*		Width (mm)*		Perimeter (mm)*		Area (mm^2)*	
Grain Type	FE	AS	FE	AS	FE	AS	FE	AS
Barley	9.0(1.7)	9.3(1.7)	3.7(0.2)	3.4(0.3)	22.9(3.1)	22.2(3.5)	23.4(3.1)	22.6(3.3)
Oats	10.8(1.6)	11.4(1.5)	2.5(0.3)	2.7(0.2)	26.1(2.8)	25.7(3.2)	24.6(4.0)	23.7(4.2)
Rye	7.4(0.3)	7.2(0.6)	2.4(0.2)	2.5(0.2)	18.1(1.8)	17.1(1.3)	15.1(2.0)	14.7(2.0)
Wheat	5.8(0.3)	5.7(0.4)	3.0(0.3)	3.0(0.3)	14.1(0.4)	14.6(1.0)	13.1(1.2)	13.7(2.0)

*Means followed by standard deviations within parentheses based on n = 75.

ations, it may be possible that kernels would align in such a manner that they would not be separated and counted correctly by the algorithm. An example of the output of the algorithm is shown in Fig. 5 in which the fitted ellipses (drawn using a graphics software package) are shown overlaid on the binary image of the grain sample.

Extracted features

The morphological features extracted using ellipse fitting to images containing touching kernels and using conventional processing of images (Nair 1997) containing separated kernels are given in Table I. The differences in all four features by both methods were statistically insignificant ($p>0.05$). This demonstrates that the ellipse fitting algorithm can be used to extract some morphological features from images of touching grain kernels.

SUMMARY AND CONCLUSION

The ellipse-fitting algorithm performs well under a variety of realistic situations. Though the elliptical models of kernels returned by the algorithm do not contain minute morphological details present on the kernel boundaries, a broad classification of the kernels can still be made. The approximate data returned by the algorithm will be of use to other algorithms which may achieve a finer classification.

In addition to its utility as a specific tool, the algorithm also introduces the significant concept that it is worthwhile to view segmentation and classification as a single problem rather than as two sequential procedures in a pattern recognition problem.

Specifically, we have shown that:

1. The method of ellipse fitting can generate single ellipses for each touching or non-touching object in an image and thus can count the number of objects.
2. From the approximate ellipses, size related features (e.g. length, width, area, and perimeter) can be calculated.

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