The Canadian society for engineering in agricultural, food, and biological systems

CSAE SCGR

La société canadienne de génie agroalimentaire et biologique

Paper No. 05-006

Separation touching grain kernel in machine vision application with Hough Transform and morphological transform

Gong Zhang

Department of Biosystems Engineering, University of Manitoba, Winnipeg, MB R3T 5V6, Canada

Digvir S.Jayas

Department of Biosystems Engineering, University of Manitoba, Winnipeg, MB R3T 5V6, Canada

James Deng

Department of Applied Computer Science, University of Winnipeg, Winnipeg, MB R3T 2M9, Canada

Jeff Halhead

Department of Computer Science, University of Manitoba, Winnipeg, MB R3T 5V6, Canada

Written for presentation at the CSAE/SCGR 2005 Meeting Winnipeg, Manitoba June 26 - 29, 2005

Abstract

A Hough transform algorithm was developed to separate touching grain kernels in images. The edge of each grain kernel in an image was segmented. Then, a variation of the Hough transform was used to locate individual grain kernels in the image. After the representative ellipses were generated by clustering, the touching grain instance was separated by morphological transform. The success rate in separating all grain touching cases as determined by visual inspection of separated images was 92.0% for CWRS wheat, 88.5% for barley, 91.0% for CWAD, and 86.5% for oats.

Keywords: Separation, machine vision, Hough transform, Grains, Morphological transform

1. Introduction

During grain-handling, information on grain type and grain quality is required at several stages to determine the next stage of handling operations. Currently, the process of manually analyzing samples is subjective and is influenced by human factors and working conditions. If a machine vision system could identify the contents of a grain sample quickly and with a high accuracy, it should allow automated systems for grain handling and grain quality monitoring. For example, a machine vision system could be used to collect information on grain types and contamination to automatically decide the type of grain cleaning device and its operating parameters. This would help increased cleaning throughput and recovery of salvageable grains.

Substantial work dealing with the use of grain physical features for classifying grains has been reported in the literature (Majumdar and Jayas, 2000a, 2000b, 2000c, 2000d; Paliwal *et al*., 1999). One of the constraints of these studies was that grain feature extraction algorithms required all kernels to be non-touching. This was necessary because the clusters of touching kernels made the feature extraction of an individual kernel impossible. For most of these studies, grain kernels were manually positioned in a non touching manner for imaging.

In practice, a grain sample presentation device, such as a vibrating bed, may be used to present the grain kernels in a single-kernel deep layer. But these devices for presenting singular kernels still can not separate all touching kernels. Crowe *et al*. (1997) used a sample presentation system consisting of a vibratory feeder and flat conveyor, to obtain the images of grains. With flow-rates near 60 g/min, about 90% of all kernels were presented as individual kernels. The majority of touching kernels appeared in groups of 2, with less than 4% of all kernels appeared in groups of 3 or 4. Therefore, it is necessary to develop an algorithm to separate touching grain kernel images to solve this problem. Also, such an algorithm should focus on separating two or three touching kernels, because multiple kernels touching instances can be eliminated by using mechanical systems (Crowe *et al*. 1997).

A mathematical morphology based algorithm was developed and tested for disconnecting the conjoint kernel regions in an image of touching grains (Shatadal *et al*.

1995a, 1995b), but, it was time-intensive and did not perform well on grain kernels with slender shape. In another study, grain kernels were approximated as ellipsoids and it was assumed every grain kernel could be represented by the approximating ellipsoid. Individual grain kernel identification could be done by finding a representative ellipse, which "represents" the silhouette of the grain kernel (Zhang et al 2005). However, accurate determination of each grain kernel area plays key role in this kind of applications for kernel separation. The Hough transform is a popular method for extracting geometric shapes. Primitives on the Hough transform are represented by parametric curves with a number of free parameters. The principal concept of the Hough transform is to define a mapping between an image space and a parameter space. Each edge point of an object is transformed by the mapping to determine related parameters such that the defined primitive passes through the data point. Because a curve with *n* parameters requires an *n*-dimensional parameter space, many applications of the Hough transform concern line and circle detection. In order to overcome the excessive time and space requirements for ellipse extraction, proposed techniques (Yip *et al.* 1992*;* Yoo and Sethi 1993; Wu and Wang 1993) decompose the five dimensional parameter space into several sub spaces of fewer dimensions. The decomposition is constrained by specifying the organization of edge data. A restricted Hough transform was used in this study for finding representative ellipse.

2. Materials and Methods

2.1 Imaging System

The hardware for image acquisition system consisted of a colour camera (Model DXC=300A, Sony), a camera control unit (Model CCU-M3, Sony), a diffuse illumination chamber with a circular fluorescent tube (305 mm in diameter, 32 W, Model FC1279/CW, Philips, Singapore) with light controller (Model FX06482/120, Mercron, Richardson, TX), and a colour frame grabber installed in a personal computer (PC). The camera captured images from the samples placed in the illumination chamber. The camera outputted three parallel analog video signals, namely red (R), green (G), and blue (B), corresponding to the three NTSC (National Television System Committee) colour primaries, and a sync signal. The acquired digital images were then stored for analysis using an IBM-compatible personal computer. All image-processing algorithms were programmed in Visual C++ (Microsoft) and Java (Sun Micro System).

2.2 Grain Samples

The grain samples for this study were obtained from the Industry Services Division of the Canadian Grain Commission (Winnipeg, MB). For the 1998 growing year, clean grain samples of CWRS wheat (Grade 1, 2, and 3), CWAD wheat (Grade 1, 2, and 3), barley (Special Select Malt Barley), and oats (Grade 1) were used to test the separation algorithm.. Samples were collected from 30 growing regions of western Canada. These growing regions were chosen using the climatic subdivisions of the Canadian Prairies (Putnam and Putnam 1970). All the samples were mixed and 500 kernels of each grain type were randomly picked and were used to create 200 touching instances for each grain type. Around 10% of all touching instances were triple touching kernels; other instances were double touching kernels. For the touching instances, one grain kernel was randomly dropped as the centre, and other kernels were manually placed to touch the centre kernel to simulate possible different touching instances. Touching instances were created to result in a point or a line contact or in between possibilities. Care was taken not to let kernels overlap. After the image of the touching kernels was acquired, the kernels were then manually separated without disturbing the orientation of the kernels. Then, an image of manually separated kernels was also acquired with the same hardware and software settings.

3. Algorithm

3.1 Segmentation and boundary extraction

An adaptive thresholding technique based on R, G, B values of image pixels and hue histograms was used to determine the threshold value. After the threshold value was determined, the pixels with gray value higher than threshold were given the value of 1 as objects; others had the value of 0 as background. Therefore, the colour image was transferred to a binary image. If a small dark region within an object fell below the threshold, this region was assigned as background and represents a “hole”. With “region growing” to find all inter-connected background pixels, the “holes” were identified and filled. An object boundary is the closed edge that surrounds a region. If a pixel’s neighbors have different values (0 or 1), it may represent an edge point. When the object boundary was extracted by the edge detection operator, the object edge pixels were tracked and stored in an ordered points list. This ordered points list were used as sample points.

3.2 Hough Transform

Representative ellipses were extracted from the image using an efficient variation of the Hough transform that accumulates on every pair of points, utilizing the positional derivatives at each point. For an arbitrary ellipse, there are five unknown parameters, (x_0, y_0) for the center, α for the orientation, (a, b) for the major and minor axis. For each pair of pixels (x_1, y_1) and (x_2, y_2), they are assumed as two vertices on the major axis of an ellipse. At the same time, they are also assumed as two vertices on the minor axis of an ellipse. Therefore, Four parameters for the assumed ellipse were estimated following:

$$x_0 = \frac{(x_1 + x_2)}{2} \quad [1]$$

$$y_0 = \frac{(y_1 + y_2)}{2} \quad [2]$$

$$a = \frac{\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}}{2} \quad [3]$$

$$\alpha = a\tan\frac{y_2 - y_1}{x_2 - y_1} \quad [4]$$

Where (x_0, y_0) is the center of the assumed ellipse at the half-length of the major axis, a is major axis, and α the orientation of the ellipse.

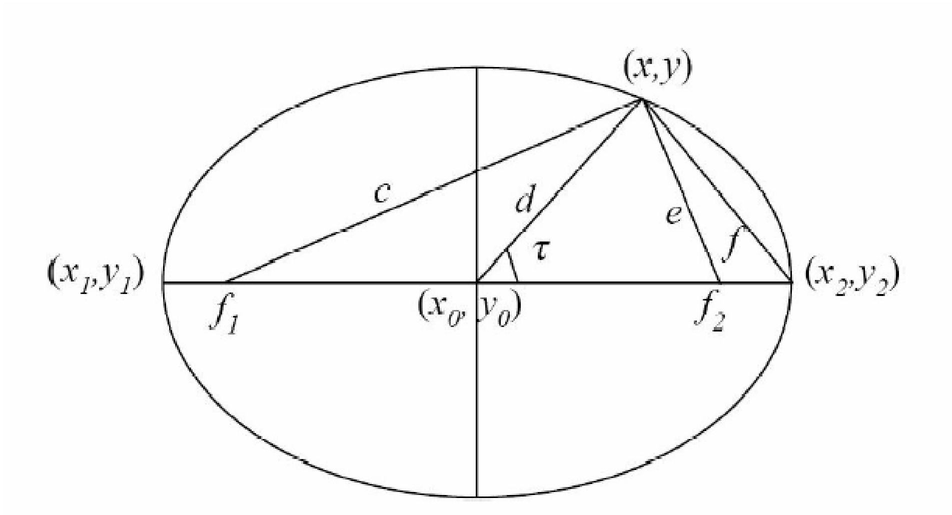

Figure 1: Shows ellipse geometry.

In Figure 1, f1 and f2 are foci of the ellipse and (x, y) is the third point used to calculate the fifth parameter.

The distance between (x, y) and (x_0, y_0) should be smaller than the distance between (x_1, y_1) and (x_0, y_0) or between (x_2, y_2) and (x_0, y_0) Thus, the half- length of the minor axis can be estimated by the following equation:

$$b^2 = \frac{a^2 d^2 \sin^2 \tau}{a^2 - d^2 \cos^2 \tau} \qquad [5]$$

Consequently, by using equations (1) – (5) it is possible to calculate all five parameters of an ellipse. Since we only need to calculate on the half- length of the minor axis, we can use a one-dimensional accumulator array. If the half- length of the minor axis was determined , an ellipse is found and the parameters for this detected ellipse are output and remove all pixels of this ellipse from the image. After this pair of pixels is checked, the accumulator array was cleared and go to the next pair.

3.3 Classifying all generated ellipses to determine the representative ellipse for each kernel.

Every trial of the ellipse fitting procedure created an inertial ellipse for the touching kernel groups. Because the Hough transform only generated the ellipses for ellipsoid similar edge curve, for a particular group of touching kernels, only 30 representative ellipses were generated compared to 100 fitted ellipses generation for fitted ellipse algorithm (Zhang et al. 2005). When a set of similar representative ellipses for every individual kernel in the touching group were generated, some extraneous ellipses were also generated. When all inertial ellipses were created, two selected criteria were applied to eliminate inappropriate ellipses. These criteria were:

- All ellipses must meet $a1 < a/b < a2$, where a is the major axis of the ellipse, b is the minor axis of the ellipse. After numerous trials to different types of kernels, the threshold $a1$ was determined as 0.3, and the threshold $a2$ was determined as 0.9.
- The measurement of overlap between the touching object and ellipse were limited as:

$$\xi = \frac{\omega \cap \varepsilon}{\varepsilon}$$

where ω is the set of touching object pixels, ε is the set of pixels of the ellipse. If the ξ >0.95, the ellipse is a proper ellipse.

In ellipse clustering, if each cluster only contained the ellipses similar to one individual grain kernel, the filtered ellipses could be grouped to clusters to determine the kernel numbers in the touching instance. For each ellipse, x_0, y_0, a, b, and θ are five main parameters, where (x_0, y_0) = center of the ellipse, a = the major axis of the ellipse, b = the minor axis of the ellipse, and θ= orientation of the long axis from the x-axis. With these five parameters, the difference and similarity of ellipses could be determined. When each parameter of an ellipse was considered as a dimension of Euclidean space, that ellipse could be identified as a point of this Euclidean space R^5. To measure the similarity between two ellipses, a distance measure based on the above features space was applied and the distance between two ellipses was defined as the Euclidean distance *d*.

The clustering was based on the minimization of a performance index, which was defined as the sum of Euclidean distances from all patterns in a cluster domain to the cluster center. For two ellipses, x_i and x_j , if $d(x_i, x_j) < \delta$, these two ellipses were considered one cluster, where δ is a threshold determined by Euclidean distance measurement of 100 touching instances. When all ellipses were classified, *K* initial clusters were generated. With each cluster, the cluster center $z_j(k)$ was obtained by: $Z_j(k) = \frac{1}{n}\sum_{i=1}^{n} x_i$ where n is the number of ellipses in each cluster. If one cluster only had a few ellipses that were less than five, this cluster was considered as an inappropriate ellipse cluster and excluded. After repeating cluster analysis, some of the clusters coalesced to create a new single cluster containing a new representative ellipse. In the end, the sets of clusters were built up and the center pattern of each cluster was the representative ellipse for that cluster. When representative ellipse had been assigned to each cluster, every kernel of the touching grain group was replaced by a representative ellipse. Moreover, when these representative ellipses were generated, these ellipses were not allowed to touch each other.

3.4 Using mathematical morphological method for separation

After every representative ellipse for each kernel of a touching case was determined, a mathematical morphological method was used to dilate the ellipses. During the dilation, these dilated ellipses were not allowed to join each other.

This method was used to grow the ellipse and prevent the neighboring expanding components from joining together. This operation applied a mixed structuring element, $L=(l_1, l_2)$. This structuring element is:

$$\begin{matrix} l_2 & l_2 & l_2 \\ * & l_2 & * \\ l_1 & l_1 & l_1 \end{matrix}$$

That is, only those pixels are included in the hit-or-miss transform of an image with mixed structuring element, L, where simultaneously the l_1 locations hit the foreground of the image and l_2 locations miss the foreground. For a pixel, if, with eight of its neighbors, at least three neighbors as defined by l_1 locations are "on" and at least three other neighbors as defined by l_2 locations are "off", this pixel was turned "on". For sequential thickening, the above configuration of the structuring element, L, and seven other rotation of this grid were used. This logic imposed during growing the ellipses prevented their merger. Sequential thickening was repeated one hundred times for each ellipse to make sure the dilating regions were big enough to cover the silhouette of the original kernels. After dilation, the dilated ellipses can cover the silhouette of the grain kernel of the touching groups. Because all these dilated ellipses are separated, using the logic "AND" with dilated ellipses and the original touching group, the touching isthmus between the kernels were identified, and the clusters of touching kernel regions in the image were separated.

4. The results of software separation

The success rate in separating all grain touching cases by visual inspection in an image was 92.0% for CWRS wheat, 88.5% for barley, 91.0% for CWAD, and 86.5% for oats. When the mathematical morphological separating algorithm (Shatadal *et al*. 1995a, b) was applied to the touching cases of long ellipsoid kernels with a longer isthmus area, like oats, it often failed because of over erosion. With the ellipse fitting algorithm, this problem was solved by using a fitted ellipse to isolate the isthmus area. Therefore, the ellipse fitting algorithm performed better in separating the touching oat kernels with 94.8% accuracy, compared to 79% separation accuracy with the mathematical morphological based separation algorithm of Shataldal *et al*. (1995a). The average separation success rate of fitted ellipse algorithm (Zhang et al 2005) is 93.5%, however, this ellipse fitting algorithm have to create quite a few fitted ellipses that were not similar to origin grain kernel edge curve. Therefore, ellipse fitting algorithm took more time to find representative ellipse than Hough transform algorithm.

Hough transform algorithm also had some limitations. The separation success rate for barley was lower because some barley kernels were not approximated as ellipsoids. For those kernels with irregular shape, some improperly ellipses were filtered during overlap measurement. However, some improperly ellipses may have passed the overlap filter and clustered to the representative ellipse. This would cause the separation line to move during dilation and place the separation line improperly. In the future, the clustering process should be improved for representative ellipse selection.

Acknowledgements

We thank Canada Research Chairs Program for funding this study.

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