An active contour computer algorithm for the classification of cucumbers

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ABSTRACT

The cucumber is one of the most important crops worldwide and, because it is generally consumed fresh, it must be classified into quality categories. The European classification system includes a parameter that relates the degree of curvature relative to the length. Until now, this classification could not been be achieved with an automatic system due to the difficulty associated with correctly calculating the axis of a cucumber. This article describes a computer algorithm that uses active contours or "snakes" to classify cucumbers by length and curvature. This algorithm demonstrates an advantage in the determination of the central line of each cucumber, based on an iterative process that is quick and carries out the classification process efficiently. The method was validated against human classification for 360 cucumbers and was also compared with an ellipsoid approximation method. The active contour method reduced the classification error by 15 percentage points, compared with the ellipsoid approximation method, to 1%, with no serious errors (i.e., misclassification of Class Extra and I into Class II or vice versa). Meanwhile, the ellipsoid approximation method led to a 16 % error rate, of which 2% were serious errors (an error of two classes). The developed approach is applicable to fresh cucumber commercial classification lines to meet the requirements of the European regulations for cucumber classification.

Keywords: Artificial vision, cucumber, curvature, grading, length, shape.

Nomenclature

C	The curvature (ellipsoid).
C_x, C_y	The centres of mass (ellipsoid).
D	An approximation of the maximum diameter (ellipsoid).
d	An approximation of the minimum diameter (ellipsoid).
$D(x, y)$	The distance transform of the image for a given pixel (x, y).
E	The energy.
E_C	The component of the energy E related to the curvature.
E_P	The component of the energy E related to the transform D(x, y).
i	Represents the iteration number.
j	The point on the axis that is moving.
k	The new position on the ordinate axis to which the point can be moved (target window).
M	The size of the window of new positions that are evaluated in each iteration.
m_{ij}	The moments of inertia $m_{ij} = \sum_{\xi} x^i y^j$ Where the summation extends over all the elements in ξ, i.e., all the “white” pixels in the image. m_{00} represents the area of the object, i.e., the number of white pixels, and silhouette moments of first-order are m_{01} and m_{10}
N	The number of points selected on the original axis.
x,y	The cartesian coordinate (points).
α	The weighting parameter for the elasticity and rigidity components of the internal energy, wth a weight adjustment of E_P in E.
β	The weighting parameter for the elasticity and rigidity components of the internal energy, with a weight adjustment of E_C in E.
γ	The angle of orientation for the centres of mass.

1. Introduction

Cucumber (*Cucumis sativus* L.) crops total 53.3 million tonnes in production worldwide (FAO, 2012a), demonstrating the global importance of cucumbers agriculturally and economically (Qi et al., 2012). The cucumber is cultivated all over the world with a greenhouse yield of 8 Kg/m^2 (Fernández et al., 2007) and between 6.8 and 7.6 Kg/m^2 under open field conditions (Simsek et al., 2005). One of the largest concentrations of greenhouses in the world is the coastal area of southeastern Spain (Agugliaro, 2007), which covers approximately 37,500 Ha (Manzano and Cañero, 2010), and is primarily dedicated to the production of greenhouse vegetables. In this area, 4,551 Ha are allocated to cucumber crops (Callejon-Ferre et al., 2011), meaning that an annual production of 364080 Tn of cucumber is sourced from this region. Cucumbers are generally consumed fresh, and hence need grading prior to the marketing.

Cucumbers are classified according to their maturity and size, as determined by market demands. Generally, classification is performed according to maturity and size. Size classification is performed manually, or by weight, using a conveyor belt system (FAO, 2012b). Cucumbers also can be classified according to the fruit form, colour and health.

The principal exporters of cucumbers are the Netherlands, Mexico, Spain, Jordan, United States, Malaysia, Belgium-Luxembourg, Greece, Canada and Germany; while the principal importers are Germany, United States, United Kingdom, the Czech Republic, France, the Netherlands, Canada, Singapore, Sweden and Austria (FAO, 2012a). The European grading standards for cucumbers are based on weight, length, shape and defect (UE, 1998).

The current quality control systems used in the agroindustrial sector have benefited from significant advances in digital imaging technology. Examples of applications using artificial vision systems for fruit classification and quality monitoring are given by Pencue and León-Téllez (2003). A wide range of studies concerning fruit and vegetable classification according to colour, size and imperfections have been carried out.

To date, artificial vision systems using hyperspectral imaging for cucumber selection have been implemented in the detection of bruises or defects (Ariana et al., 2006), selection by colour (Ariana and Lu, 2010a), and the identification of internal defects to designate cucumbers for pickling (Ariana and Lu, 2008a and b; Ariana and Lu, 2010b; Lu et al., 2011). Additionally, visible and near-infrared measurements have been used to determine firmness, skin and flesh colour, as well as the dry matter content of pickling cucumbers (Kavdir et al., 2007).

Van Eck et al. (1998) developed a method for the automated assessment of cucumber fruit length and width, as well as the length and shape of the necks of fruit oriented to inflection points of the skeletonised fruit area. By this approach, they were able to determine the local width along the mid-line of the fruit, enabling a condensed description of the fruit to be provided. From this condensed description, the size and shape features can be extracted, such as the length, width and neck-shape of the cucumber fruits. This work was based, in part, on that of Howarth et al. (1992), which was developed for carrots. In this work, the change in the outline of the image was determined by a change in direction of the outline pixels.

Kang et al. (2006) developed a quality evaluation system for the classification of cucumbers based on measurements of length and curvature, thereby allowing the removal of tapered and dumbbell shaped cucumbers based on the changes in girth (thickness). From the girth calculations, cucumbers could be classified as straight, cudgel or dumbbell shaped. The curvature was calculated using the Hough transform (Ballard, 1981). From the curvature data for an individual cucumber fruit, its bowing (S-shape) was determined.

It is noteworthy that to date there are no published articles on the determination of cucumber curvature in relation to the axis length, although this feature is required for correct classification. The active contour model (i.e., a snake algorithm) has been employed in agricultural purposes for refinement in segmentation to improve the localisation and size accuracy of blemishes detected on apples (Yang and Marchant, 1996). However, for curvature determination purposes, there also have been several interesting applications, such as that proposed by Schmidt et al. (2012) as a variational approach for simultaneously tracing the axis of tubular surfaces or by Wang et al. (2009) for modelling the contours of worms, obtaining smoother and more accurate centre lines of worm forms than by skeletonising of binary masks.

The objective of the present study is to propose a method based on active contour assessment for cucumber classification and to evaluate it against the existing European classification regulations. We present a non-destructive metrology able to give grading information concerning the product. The system used digital imaging technology working within the visible spectrum, assessing the external aspects of the fruit and undertaking a classification of curvature, length and weight in accordance with the quality control parameters mandated by international regulations. We give a description of two methods implemented and the results of both are evaluated.

2. Materials and methods

Cucumber classification was undertaken based on three basic parameters, including weight, length and curvature, consistent with European regulations (UE, 1998; see table 1). The difference between the Extra and first (I) classes lies in the fruit defects (UE, 1998). Fruit in the

Extra category possess no defects, while category I allows some defects. The current study does not analyse defects; hence, we make no distinction between these two classes.

The classification process involves various steps and culminates with the use of protective packaging for commercialisation (see fig. 1). The process begins when the vegetables arrive at the packing station where the cucumbers are packed in crates for protection and handling after they leave the greenhouses. The products are unloaded onto conveyor belts and pass through a shrink wrap tunnel in which each piece is individually encased with plastic film. Then, the conveyor belt moves the cucumbers over a load cell, where each piece is weighed, storing its weight as the starting point for the classification process. The classification phase employs digital imaging technology to assess length and curvature. According to the results, each cucumber follows a distribution line to its appropriate packing station, where a separate robot arm on each of the distribution lines automatically picks up the cucumber and places it into the final packing carton. The final step is to stack the packing cartons on pallets for transport to the reception centre.

Table 1

The classification system developed in this paper begins with the weight of each piece, which information is provided by an external weighing system (the load cell on the conveyor belt). The use of such systems for vegetable classification by weight is very common today (Clement et al., 2012); hence, the system is not discussed further in this paper.

The present study focuses on the classification of cucumbers on the basis of length and curvature by means of artificial vision. Since defects detection was not considered in this work, no distinction has been made between Extra and I classes. The following two methods were applied for estimating the length and curvature of cucumbers from the images.

- Method 1: Ellipsoid Approximation. This is an adaptation of existing methods developed for the classification of other fruits and vegetables (Clement et al., 2012).
- Method 2: Successive or Evolutive Approximation. This method is based on assessments of weight and energy.

We consider a grading error when a cucumber it belongs to one adjacent class (+/- 1 miss) or two classes away from the true class (severe miss).

2.1. Method 1: Ellipsoid Approximation

One way to represent the parameters of length and curvature of a cucumber is by approximating its form as an ellipsoid. Thus, each cucumber is represented by the ellipse that best approximates its specific outline, while the ratio between the long semiaxis and the short semiaxis provides information regarding its curvature. In this manner, the problem is reduced to detection of the fruit edges and to obtaining its central moments m_{ij}. The central moments are used to make approximations of maximum diameter (*D*), minimum diameter (*d*), and curvature (*C*) (Rocha et al., 2004):

$$C = \frac{D}{d} \quad (1)$$

$$D = \sqrt{\frac{2(m_{20} + m_{02}) + \sqrt{(m_{20} - m_{02})^2 + 4m_{11}^{\;2}}}{m_{00}}} \quad (2)$$

$$d = \sqrt{\frac{2(m_{20} + m_{02}) - \sqrt{(m_{20} - m_{02})^2 + 4m_{11}^{\;2}}}{m_{00}}} \quad (3)$$

Implementation of this method uses an image captured in grey-scale in which the region of interest (ROI) is identified. The ROI has fixed dimensions and location because the image capture process in artificial vision uses a synchronised signal that always is activated when the cucumber reaches a particular position. Once the ROI is identified, a threshold is created for each region, eliminating the background and leaving only the outline of the product. The outline is subsequently used to detect the product edges. From the outline of each piece, the central moments are obtained in addition to identification of the ellipsoid using one of the above expressions (equations 1-3).

The overall image processing approach is summarised in fig. 2.

The characteristics of the cucumbers shown in fig. 2 are described in table 2, and the results using the ellipsoid approximation method are shown in the same table.

Table 2

With this method, it can be observed that the ratio between the ellipsoid's axes can be used to indicate the degree of curvature of the cucumber, although the ratios between this descriptive parameter and the actual curvature are neither equivalent nor inversely proportional. Additionally, the errors in both the length calculation and the curvature increase with greater object curvature. Nevertheless, certain numeric values can be established that allow the cucumbers to be classified into categories as a function of the ratio between the axes of the ellipsoids obtained following the first method. The threshold values used to establish the categories were obtained empirically and are presented in table 3.

Table 3

2.2. Method 2: Method of Successive Approximations (Active Contours or "Snakes")

Given an elongated curved shape, the objective of method 2 is to identify the axis such that its points lie at equal distance from the opposite edges of the object (fig. 3B). We start with a straight axis, which possesses the smallest moment of inertia (fig. 3A); here, the initial distances are $r_{i,j}$ and $r_{i+1,j}$, and the difference between them is $\Delta r_{i,j}$. This axis is refined successively to approach that shown in fig. 3B, moving each of the points perpendicularly with the goal of obtaining equivalent distances from each opposing edge (D_j).

This is achieved by calculating the distance transform of the image for the area inside the object's outline, where each pixel represents the distance of a point to the nearest border (fig. 3C).

Next, an algorithm similar to the active contours algorithm is applied; active contours, or snakes, were developed by Kass et al. (1988), and the method is widely used in artificial vision for recognising shapes (e.g., Kovacs and Sziranyi (2012)).

For each point on the starting axis, two forces are applied. One pushes the point in the direction of the gradient of the distance transform, i.e., in the opposite direction to the nearest border. The second limits the curvature of the line, making it as gentle as possible. This procedure is applied successively to each point along the axis until convergence is reached. For calculation of the energy of each point, the following expressions are used:

$$E_{ij} = \min_{k=2 \ldots M-1}\left(E_{ijk}\right) \quad (4)$$

$$E_{ijk} = \alpha \cdot E_{Pijk} + \beta \cdot E_{Cijk} \quad (5)$$

where α is a weighting parameter for the elasticity and rigidity components of the internal energy, given a weight adjustment of E_P in E; and β is the weighting parameter for the elasticity and rigidity components of the internal energy, with a weight adjustment of E_C in E.

$$E_{Pijk} = D\left(x_j, y_{jk}\right) \quad (6)$$

$$E_{Cijk} = \left(y_{j-1} - 2 \cdot y_{jk} + y_{j+1}\right)^2 \quad (7)$$

where *i* represents the iteration number, *j* refers to the point on the axis that is moving, which can take a value of 2 to (*N* -1), where *N* is the number of points selected on the original axis, such that the two extremes are always fixed. The index *k* refers to the new position on the ordinate axis to which the point can be moved; *k* varies from 1 to *M*, where *M* is the size of the window of the new positions that are evaluated in each iteration. *D(x, y)* represents the value of the distance transform of the image for the pixel (*x*, *y*). The values of *M* and *N* depend on the pixel resolution of the image and on the size of the object relative to the background. In our case, the values are given as *N* = 51 and *M* = 11 for an image of 640 x 480 pixels.

Fig. 4 represents the results obtained for samples 1 and 3, represented in fig. 2.

In fig. 4, the process used based on the method described here is represented. First, the image is reorientated and the binarised image is centred; this step uses the image calculated in the previous step, further utilising the information of the centre of masses (C_x, C_y) and the angle of orientation (γ), which can be extracted from the moments of inertia according to expressions (8) and (9).

$$\gamma = \frac{1}{2} \cdot \tan^{-1}\left(\frac{2 \cdot m_{11}}{m_{20} - m_{02}}\right) \quad (8)$$

$$C_x = \frac{m_{10}}{m_{00}}; \quad C_y = \frac{m_{01}}{m_{00}} \quad (9)$$

In an actual automatic calibration system, the reorientation and centring steps can be avoided because the product can be mechanically oriented according to the arrangement of the distribution line.

Next, the distance transform of the image is performed. The starting axis used is the line that joins the points of the image (fig. 4A) at the extreme right and extreme left ends; the value of this line is non-zero. The length of this axis approximates perfectly the length of the cucumber, as represented by the solid line in fig. 4C. The same figure also shows the points of the axis after the required iterations have been performed. In each case, and with values of α = 2 and β = 1, no more than 30 iterations were required; typically, 10 iterations was found to be enough. Although the software allowed regulation of the number of iterations, in this case, deviation of the curvature can be approximated by the maximum distance between the starting and final axes of curvature.

The results obtained using this method for the three starting samples (table 1) are given in table 4.

Table 4

In this case, a significant improvement can be observed in the approximation of curvature and the associated ratio; the improvement is directly proportional to the real values.

2.3. Classification Software

The classification software used was entirely developed in the C++ language, using the open code libraries for image processing, OpenCV 2.3.1 (Opencv, 2012). These libraries allow direct use of simple image processing tools, such as threshold, moments, find contours, etc., which work satisfactorily. The graphic user interface was developed using the Nokia QT libraries (QT, 2012), which contain a large number of graphics functions. Additionally, these libraries have a wide repertoire of communication functions, which facilitates integration of this application with external automatic systems. Using these two libraries, software was developed that permits the image to be captured and the process undertaken to be partially configured, as well as graphical representation, storage and communication of the results.

3. Experimental validation

In the experimental part of this study, we evaluated our proposed methods quantitatively using 100 kg of cucumbers, comprised of 360 pieces. This quantity was selected based on previous studies in which a total of 150 cucumbers were considered sufficient to validate the model (Kang et al., 2006). Dutch cucumbers were chosen: this type is typically long with smooth, slightly grooved skin. The results are presented according to each method, and comparisons were made against the true classification for each cucumber.

Table 5 shows the classification resulting from each method and indicates some differences with respect to the true classification made by expert operators. A significant number of errors were made during classification: in some cases, a cucumber truly belonging to one class was classified as belonging to an adjacent class (+/- 1 miss), or in some cases, the assigned class was two classes away from the true class (which is denoted as a severe miss). Table 6 represents the percentage of errors committed due to the different causes and summarises the errors by method and cause (length, curvature or both).

Table 5

Table 6

4. Discussion

The active contour model (i.e., the snake algorithm) has been employed in various agricultural purposes, such as refinement of the image segmentation (Yang and Marchant, 1996) or the determination of the central line, the axis of tubular surfaces (Schmidt et al., 2012), or worm forms (Wang et al., 2009). However, this approach has never been used to determine the central line of agricultural products like cucumbers as a means of grading purposes. For this reason, the algorithm developed here, which is based on active contours, is particularly intriguing.

The recognition of cucumber shape has not been particularly well developed, except for classifications based on length and thickness (Van Eck et al., 1998). The method presented here involves resampling the image at each point of the cucumber skeleton, perpendicular to the estimated angle of direction. The resampling width is chosen to be large enough to cover the thickest cucumber. The resulting image contains a straightened cucumber with its length equivalent to the curved length of the mid-line of the original cucumber. This method does not calculate the curvature as a function of length, and it is not suitable for implementation on a commercial sorting line because it requires double sampling of the image, including both normal and perpendicular directions.

However, the method proposed by Kang et al. (2006) for length and curvature assessment is typically used for classification of shape according to changes in width. In this way, it establishes three categories, straight, cudgel and dumbbell shaped, in which the aim is to remove the tapered and dumbbell-shaped cucumbers using the changes in thickness as the sorting criterion. In terms of curvature, this feature is used to determine the bowing (S-shape) of the cucumber. As in the above example, this work was not aimed at commercial classification based on the length to maximum curvature ratio of the cucumber.

The sampling of 360 pieces used in the present study is considered sufficient because other studies used fewer than half this number to validate their method for cucumber classification (Kang et al., 2006).

The image analysis application was designed to be an effective and objective method for automated assessment of the characteristics used in the European classification of cucumbers (EU, 1988). The advantage of an automatic method using artificial vision is that it facilitates, for the first time, an automatic classification of fruit curvature with respect to length. In particular, this aspect is very difficult to evaluate, even for experienced line operators because the thickness of the cucumber effectively disguises its curvature.

Of the two methods analysed, the first, which is based on ellipsoid approximation, was effective in only 84 % of cases. This was because, when the curvature of the cucumber exceeds a certain ratio (see fig. 2C), the method is not capable of correctly estimating the axis of the cucumber.

Additionally, we observed a 2 % rate of serious errors (an error in classification by two categories).

The second method was 99% accurate, which is attributed to a better approximation of the axis using the proposed algorithm that is based on active contours or "snakes" (Kass et al., 1988). Furthermore, the second method did not yield any serious errors (missing by two categories).

We suggest that the second classification method is likely to be more accurate than the method of manual classification because manual sorting is influenced by many factors, including the worker's subjectivity and their degree of fatigue in addition to the already-mentioned peculiarity that the girth of the cucumber masks its curvature. This feature was also observed by Van Eck et al. (1998). Curvature is an especially important feature because cucumbers are typically destined for the export market in which they are generally eaten fresh by a very discerning market.

5. Conclusions

This article develops and validates an active contour or "snake" algorithm, which is used to detect the axes of cucumbers using an artificial vision system. The method achieved 99% accuracy in the calculation of cucumber curvature as a function of length. Its development is applicable to commercial sorting lines of fresh cucumbers, as laid down by European regulations for classification that include the curvature of the cucumber as a function of its length.

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Table 1

Classification of cucumber by weight and length according to European regulations (UE, 1998).

Curvature	**Weight (gr)**	**Length (cm)**	**Category**
< 10 mm for every 10 cm length	> 500	> 30	EXTRA or I
		< 30	II
	250 – 500	> 25	EXTRA or I
		< 25	II
	< 250	-	II
< 20 mm for every 10 cm length	-	-	II
> 20 mm for every 10 cm length	-	-	III

Table 2

Values obtained using the Ellipsoid Approximation method for the samples.

		Actual sample values		Ellipsoid Approximation method	
Sample	**Category**	**Length (mm)**	**Curvature (mm/cm length)**	**Length calculated (mm)**	**Ratio between axis**
1	I	256	2 / 25.6 = 0.08	255.8	6.69
2	II	238	26 / 23.8 = 1.09	238.6	5.58
3	III	251	92 / 25.1 = 3.67	278.8	4.06

Table 3

Cucumber classification threshold values based on the ratio between major and minor axes calculated using the ellipsoidal approximation method.

Category	Curvature according to regulations (mm/cm of length)	Ratio between axis of the ellipsoid (D/d)
I	< 10/10	> 5.65
II	< 20/10	> 4.95
III	> 20/10	< 4.95

Table 4

Values obtained using the method of Successive Approximations or Active Contours for the samples described in table 1.

Sample	Length calculated	Curvature (mm/cm length)	Category
1	256.1	0.09	I
2	238.4	1.08	II
3	251.4	3.80	III

Table 5

Classification results for cucumbers using the three methods.

METHOD	Category Extra/I (pieces)	Category II (pieces)	Category III (pieces)
By experienced operators	247	84	29
Ellipsoidal	232	95	33
Active Contour	248	85	27

Table 6

Errors committed using each method and cause of the error by percentage and pieces.

Method	**Error in percentage**			**Type of error in pieces**			**Total errors**
	Exact	±1 miss	Severe miss	Curvature	Length	Both	
Ellipsoidal	84.2	13.9	1.9	39	5	13	57
Active Contour	98.9	1.1	0	2	1	0	3

FIGURE CAPTION

Fig. 1. Phases of classification for fresh cucumbers.

Fig. 2. Method of ellipse approximation. (A) Original image, (B) Threshold , (C) Borders of the image and axis of the approximated ellipse.

Fig. 3. Method of Successive Approximations (Active Contours). (A) Starting Axis, (B) Objective Axis, (C) Distance Transform of the image.

Fig. 4. Method of Successive Approximations (Active Contours). (A) Binarized image, orientated according to axis, (B) Distance Transform, (C) Starting Axis (continuous line) and axis of curvature (dotted line).