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# In-line sorting of irregular potatoes by using automated computer-based machine vision system

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This study was conducted to develop a fast and accurate computer-based machine vision system for detecting irregular potatoes in real-time. Supported algorithms were specifically developed and programmed for image acquisition and processing, controlling the whole process, saving the classification results and monitoring the progress of all operations. A database of images was first formulated from potatoes with different shapes and sizes, and then some essential geometrical features such as perimeter, centroid, area, moment of inertia, length and width were extracted from each image. Also, eight shape parameters originated from size features and Fourier transform were calculated for each image in the database. All extracted shape parameters were entered in a stepwise linear discriminant analysis to extract the most important parameters that most characterized the regularity of potatoes. Based on stepwise linear discriminant analysis, two shape features (roundness and extent) and four Fourier-shape descriptors were found to be effective in sorting regular and irregular potatoes. The average correct classification was 96.5% for a training set composed of 228 potatoes and then the algorithm was validated in another testing set composed of 182 potatoes in a real-time operation. The experiments showed that the success of in-line classification of moving potatoes was 96.2%. Concurrently, the well-shaped potatoes were classified by size achieving a 100% accuracy indicating that the developed machine vision system has a great potential in automatic detection and sorting of misshapen products.



## 1. Introduction

Although the most important quality parameters of a product include sensory attributes, nutritive values, chemical constituents, mechanical properties, functional properties and defects, the consumer's preferences depend primarily on the overall appearance, color and shape of the product. Potato (*Solanum tuberosum*) – the fifth most important crop in the world with a total harvested area of 18.9 million hectares (FAO, 2004) – can vary tremendously in size, shape and regularity. The wide variation in size and shape, and vulnerability to damage makes the potato crop a difficult one to handle and grade. Regular-shaped potatoes are preferable because the irregular ones cause a great deal of losses during peeling and subsequent processing. A product with a good appearance, size and uniform shape will always be preferable to most consumers and will have a better sales appeal. Therefore, grading and sorting processes will ensure that the products meet defined grade and quality requirements for sellers and provide an expected level of quality for buyers.

Discarding damaged and misshapen tubers is usually performed manually by workers who stand along the conveyor systems and remove all undesirable tubers based on their empirical knowledge. The potato-packaging industry is facing many labor-related problems such as rising labor costs and production waste owing to inconsistent sorting and grading and human errors (Zhou et al., 1998). Besides its inconsistency, variability and subjectivity, the manual process is very tedious, laborious, and costly, and is easily influenced by surrounding environments (Razmjooy et al., 2012). Since the efficiency and effectiveness of quality inspection processes determine the marketability of the product, there is a need for robust, automatic, consistent inspection systems to increase production speed and to improve the accuracy and efficiency with an accompanying reduction in production costs. As a result, during the past two decades, inspection of fresh fruits and vegetables by computer-based machine vision has increasingly gained ground to its manual labor counterpart at most packinghouses in the developed countries (Moreda et al., 2012).

Computer-based vision technology provides a high level of flexibility and repeatability at relatively low cost with fairly high plant throughput with superior accuracy. With recent advances in computer technology, modern manufacturers have turned their attention to machine-vision inspection systems (Sylla, 2002). Hence,

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this kind of systems is being developed as an integral part of food processing plants for real-time quality evaluation and quality control and is being used widely for the inspection of many types of foods (Cubero et al., 2011). These systems offered various solutions for some inherent problems in automation and control of many agricultural commodities (Ureña et al. 2001; Aleixos et al., 2002; Blasco et al., 2009a; Jarimopas and Jaisin, 2008; Al-Mallahi et al., 2010; Kondo, 2010; AlOhali, 2011). However, for these systems to be successful and useful in the potato business, improvements in grading and sorting speed as well as the ability to detect external (bruises, chilling injuries, blemishes, rots, etc.) and internal defects (black heart, frost damage, water core, internal cavity, etc.) are needed. These could be achieved by integrating both imaging and spectral techniques in one system called imaging spectroscopy or spectral imaging (ElMasry and Sun, 2010; Li et al., 2011). In addition to image processing regimes as the corner stone of designing all machine vision systems, mechanization is another paramount challenge in applying machine vision for food quality evaluation to transfer the decisions made by the imaging algorithm and for synchronization, separation, grading and sorting processes. Therefore, the main approach was how to implement all image processing routines in an in-line mode to perform the essential operations in a term of milliseconds and how to evaluate several products in one second instead of taking several seconds to evaluate one product. This approach requires overcoming all computational complexity.

Potatoes must have good coloration, be uniform and regular in shape and be free from any defects to gain a reasonable share in the highly competitive markets. Tubers infected by some pathogens such as infections from viruses or viroids causes a dramatic change in the tubers' shape. Among all criteria of sorting and quality inspection, shape is one of the major concerns and causes complex problems for potato inspection because of the huge variation in product shape and irregularity. In addition, damage and cuts during harvesting and handling processes adds extra types of shapes (Ding and Gunasekaran, 1994).

Shape is one of the most common object measurements for food quality evaluation during grading and classification in order to offer the consumer with homogeneous lots of products. Hence, one of the requisites stipulated by fresh produce marketing standards to qualify a fruit as a premium grade is effectively applied in packinghouses, where graders judge fruit shape depending on whether or not it detracts from the typical characteristic shape of the variety. Malformation or misshapenness expresses differently depending on the product (Moreda et al., 2012). Because of the large diversity of potato shapes, it was difficult to summarize the shape categories of this product. This property is generally referred to as the profile or physical structure of objects geometry (Jain, 1989). There are various techniques for shape description that have been investigated for food quality evaluation such as chain code, polygonal approximation, moment, etc.

Among these techniques, most applications are based on Fourier descriptors and invariant moments since they present invariance regarding the orientation, shape or size (Menesatti et al., 2008; Blasco et al., 2009b; Costa et al., 2009; Mebatsion et al., 2012). However, the estimation of the Fourier transform is very costly in terms of computational resources. To overcome this problem, the fast Fourier transform (FFT) can be used instead.

The overall objective of the current study is to develop a computer-vision system for automatic classification and grading of potato tubers in real-time based on the regularity of the shape while they are transported by an electronic sorter. This requires development of fast algorithms to analyze the shape of potatoes in order to implement it in a real-time grading system based on computer vision capable of detecting misshapen potatoes. The irregular potatoes will be discarded and the good ones should be graded by size in order to separate them into different categories. The system developed has been tested in a complete sorting machine used as a precompetitive industrial prototype.

## 2. Materials and methods

### 2.1. Potato samples

Potatoes were purchased directly from a packinghouse (Patatas Aguilar, S.A., Valencia, Spain) which carries out the grading and sorting processes either manually or mechanically. During the process inside the packinghouse, the potatoes were mechanically cleaned and washed to remove all dirt and clay clouds and then transferred in front of workers to pick up sprouted, infected, damaged and all undesirable tubers. In this study, rather than sampling the potatoes randomly we intentionally selected tubers of various sizes and shapes as a training/learning set to cover as much as possible the full spectrum in potato size and regularity. Indeed, establishing discrimination boundaries using shape information usually requires inspection and grading by an experienced human expert. The tubers were first classified manually by a professional inspector into regular and misshapen (irregular) tubers. The judgement of a good shape or a misshapen potato was performed from a viewpoint of the regularity of the tuber shape. The irregular potatoes could include any potato suffering from serious cuts, misshapen or with the presence of secondary-grown tubers called bead-like tubers or secondary tubers. Fig. 1a shows some examples of these misshapen potatoes. The training set consisted of 228 potatoes, of which 190 were voted as regular tubers and 38 tubers were voted as irregular ones. A database of images was elaborated by acquiring an image for each potato by placing them individually inside the lighting chamber over the conveyor belt. All images were then saved on the computer to be used as a database to extract the main features of each potato and to build a linear discriminant analysis (LDA) model to predict potato regularity. During the learning mode, the features extracted from the database images of known shapes were analyzed to predict the regularity of unknown sets of potatoes. Therefore, another set of potatoes consisting of 182 with 162 regular tubers and 20 misshapen tubers were collected as a testing set to validate the prediction model in a real-time application and to evaluate the accuracy of the trained machine vision system to perform such tasks.

### 2.2. Machine vision system, image processing and classification algorithms

The machine vision system used in this study as shown in Fig. 2 comprises of a CCD camera (Sony XC003P), a frame grabber (Matrox Meteor), a lighting chamber, a roller conveying system and a computer of four RAM memory and processor speed of 2.66 GHz. The camera was mounted on the top of the lighting chamber. The frame grabber digitized the images in RGB (red, green and blue) format and transferred them to the computer's memory. The lighting chamber was made from a stainless steel box. Inside this chamber, 16 40 W daylight compact fluorescent tubes were fixed to both sides and on the top of the chamber to provide homogenous lighting on the inspected tubers as they passed below the camera. Illuminating tubes were used together with high frequency electronic ballast (Osram, Quicktronic professional QTP) to avoid the flicker effect. A well-chosen lighting system allows the potatoes to be recognized and analyzed properly. Hence, it is important to avoid directional light over the potatoes in order to avoid bright spots and specular reflections that can hide or alter important features on the surface of the potatoes. Due to the variation in potatoes' shape, it is not possible to avoid this reflection;

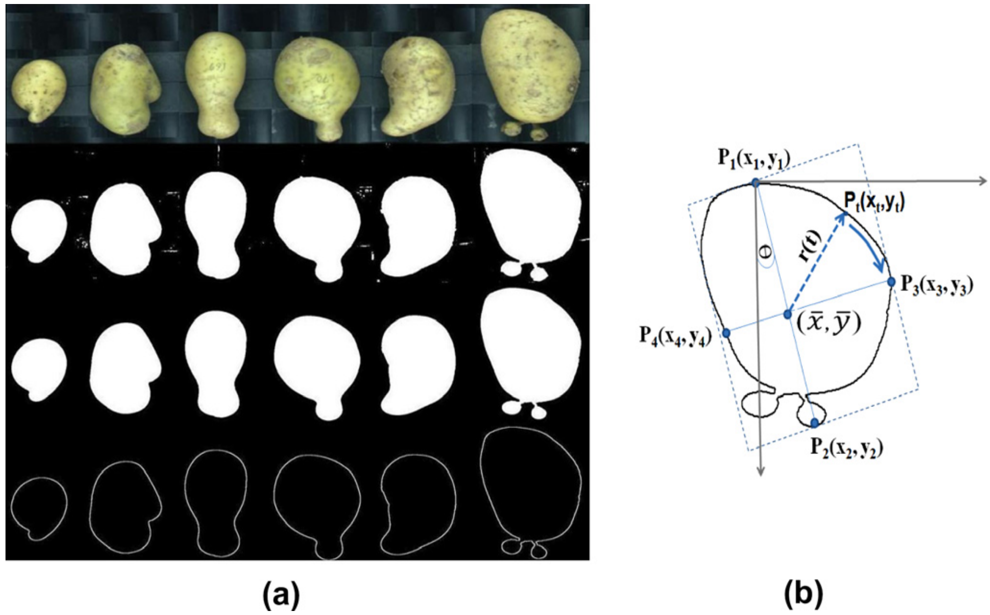


**Fig. 1.** Steps of the processing of images. (a) the first row shows original images of some irregular potatoes moving on the conveyor belt, the second row is the segmentation of tubers from the background, the third row is the segmented image after median filtering and the fourth row is the boundary edges of each tuber; (b) identifying the axis of inertia, coordinates of boundary points, centroid and major and minor axes in addition to extracting the boundary profile $r(t)$ from the boundary to the centroid.

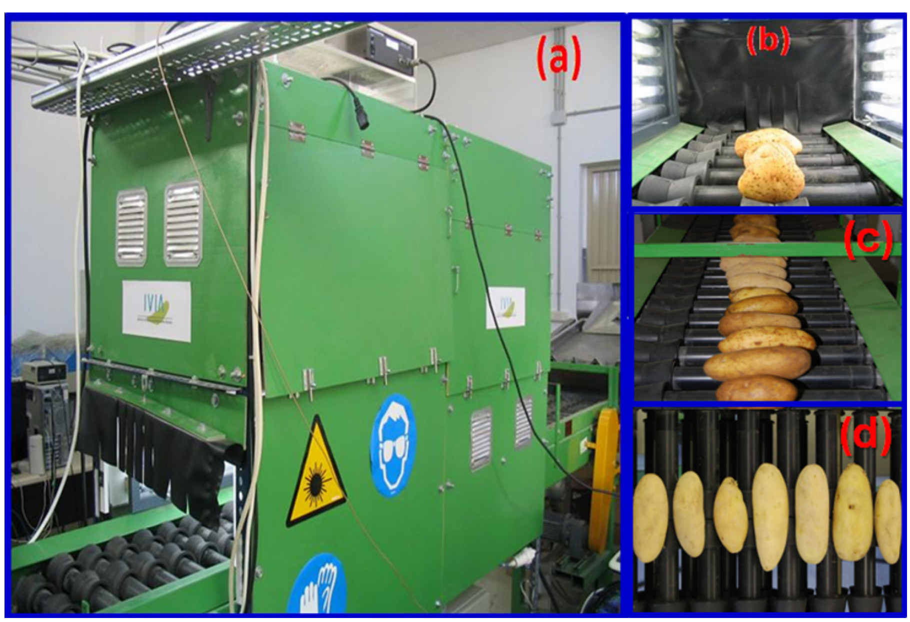


**Fig. 2.** The experimental machine vision system. (a) General layout of the machine-vision prototype showing the lightening chamber, conveyor belt, camera controller and the computer; (b) close-up view of the lightening chamber showing the lightening tubes with polarized filters fixed in front of the tubes, (c) potatoes during movement in the conveyor belt in the full capacity of the system and (d) plan view of the potatoes moving on the bi-conical roller belt.

however, this problem was radically alleviated by means of cross-polarized filters placed over the fluorescent tubes and in front of the camera lens.

The conveying system is a part of an automatic inspection and handling machine consisting of a very long conveyor with two lines of bi-conical rollers with a rotational movement that transports the tuber individually. The conveyor is capable of rotating and transporting the tubers simultaneously, allowing them to be imaged by the camera in all positions and sides, hence allowing the inspection of all tuber surfaces. Although the conveyor has two lines of bi-conical rollers, only the middle line was exploited in this study. To freeze the movement and to obtain clear images of the potatoes, the shutter of the camera was set at 1/500 s. The color of the conveyor rollers was completely black to enhance the contrast between the rollers and the tubers in order to make the segmentation process of the images easier. All of the above mentioned units were entirely controlled by the computer.

All routines for image acquisition and concurrent image processing algorithms were programmed in C language. A special graphical user interface (GUI) was designed to control the whole process, to save the classification results and to monitor the progress of all operations. All source codes were written specifically for this application without the use of any custom-built library in order to insure the control of the operations and real-time responses. A full depiction of the key steps involved in image processing algorithms for detecting misshapen potatoes is shown in the flow chart presented in Fig. 3. The algorithm had various steps of processing. The first step was for image acquisition and image pre-processing. The second step was for geometrical feature extraction such as perimeter, centroid, area, moment of inertia, length and width. The third step was for calculating shape parameters either from size features or from Fourier transforms. The most important stage was the discriminant analysis phase in which all extracted parameters were entered in a stepwise linear discriminant analysis to obtain the most important parameters that most characterized potato shape and then formulating the discriminant functions for identifying unknown shapes. If the potatoes were identified to be irregular in shape then they were classified as misshapen potatoes, meanwhile if they were identified as regular potatoes then they were graded up to four grades based on their size.

### 2.2.1. Image acquisition

The system continuously acquires images of 768 × 576 pixels with a resolution of 0.71 mm/pixel, in which the acquisition time for one image for a certain scene was 40 ms. To accelerate the system in order to perform all processes in a real-time, the acquired image was processed at the same time as acquiring a new image simultaneously which saved this 40 ms required for the acquisition, making it possible to perform the classification in an on-line mode. This was done by using two memory buffers to allocate the images in the image acquisition algorithm. Once one image was acquired in one buffer, the system started to process it while, at the same time, the camera was grabbing the next image in the other buffer. When the first image was done, the information was released from the buffer so that it can take another image.

During acquisition, the potatoes were being transported by the conveyor belt at a speed of 1 m/s while the camera continuously acquires several images for each potato from all possible sides to insure maximum surface inspection. Since the potatoes are rotating during movement, several images (views) were acquired of different sides of the potato. The total number of images acquired for each potato throughout the camera's field of view was about 5–7 images depending on the size of the potato. Once the tuber entered the field of view of the camera it is digitally labeled and tracked in their consecutive views. These views were not considered as a tuber unless the entire surface appeared in the field of view. Then, each partial image (view) was processed separately. The rollers have a separation of 80 mm. An image containing seven whole views could lead to the problem of gapping or overlapping between consecutive images. In this case, the actual scene can contain seven complete potatoes (optimum case) or six complete potatoes plus two partial potatoes touching the image borders at both ends of the image. The algorithms were capable of detecting these cases and discard them from the analysis, thus analyzing only the views of the complete potatoes. Once the last image of a particular potato is collected, the algorithm estimates the features of that potato based on the partial results of all the images processed. The frame acquisition rate was chosen to prevent gapping between consecutive images that can only occur if an image is missing (which should never happen). In any case, if this did happen as a result of a technical problem, the algorithm will miss only one view of the five to seven views of each potato and will use the rest for the analysis.

To synchronize the image acquisition with the advance of the conveyor belt, an incremental encoder (Wachendorff WDG 40S) attached to the rotating roller of the machine and connected to the parallel port of the computer was used. The encoder has a resolution of 3 pulses/mm. Knowing the distance of 80 mm between rollers, the software triggered the camera each 240 pulses, to capture

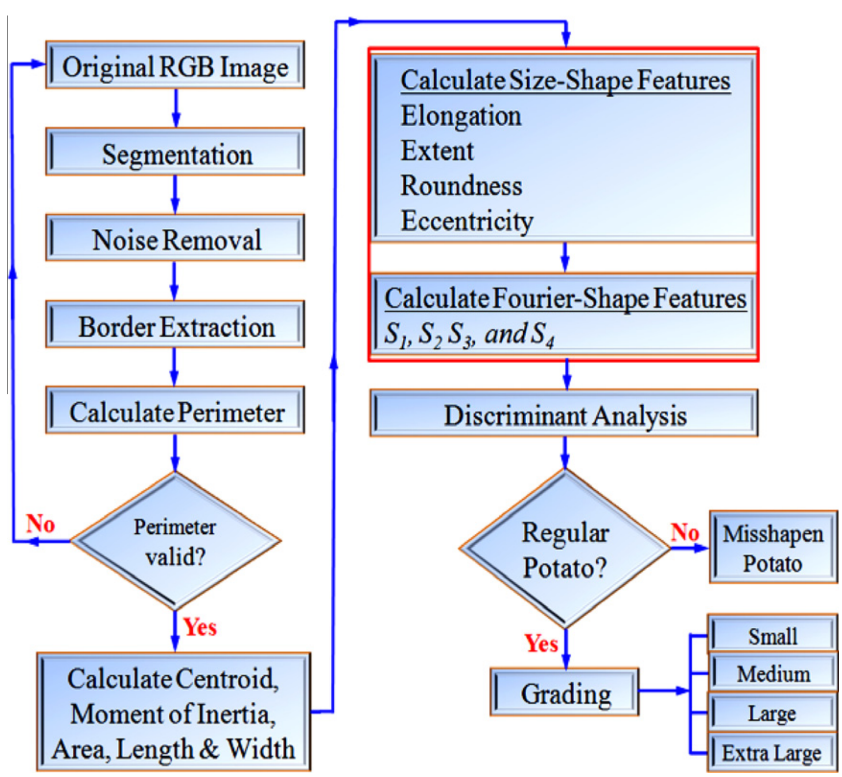


**Fig. 3.** Flowchart of the key steps of image processing algorithm for detecting misshapen potatoes.

one image for each roller entering in the scene. This allowed also tracking the position of each potato in the machine any time until it is delivered. Internally, the information of each potato is stored in an array that stores the data obtained from each view. When the last view is analyzed, the information is combined and the algorithm creates a count of pulses left to reach the proper outlet. This count is decreased each pulse of the encoder until reaching the value zero, when the potato should be delivered.

### 2.2.2. Image pre-processing and segmentation

In the first step, the image is segmented to separate the potato from the background (the conveyor). Segmentation determines which regions of the image correspond to the background and which represent the tuber itself. Since this machine vision configuration produced a high contrast image, it was possible to accurately perform segmentation by using a simple global threshold in the red channel. The threshold value was chosen according to pixels, with values below this threshold considered as belonging to the background. This resulted in a binary image in which the object (the potato) was represented in white (ones) and the background in black (zeros). Indeed, the dirt and discolored parts of the conveyor produced some scattered noise in the image which required a noise-removal routine. These noises degraded the quality of the binary image and consequently cannot provide correct information for subsequent image processing and edge detection. A median filter of size $5 \times 5$ pixels was used to remove this noise and the result was shown in the third row of Fig. 1a. A median filter is a non-linear filtering technique which allows the edges to be preserved while filtering out the unwanted noise. It replaces the output pixel with the median of its neighboring pixel values instead of a weighted sum of those values. After segmentation and filtering, the chain-code algorithm was applied to detect the potato edge and to recognize the coordinates of all perimeter pixels in the boundary. The fourth row of Fig. 1a illustrates the boundary or contour images of some misshapen potatoes using the above morphological operations. The resulting boundary image was then used to calculate the perimeter, moments and finally the Fourier descriptors of the potatoes to express their shapes.

### 2.2.3. Geometrical feature extraction

After segmentation, the next step was to extract image features that are useful in describing the potato shape. The perimeter of a potato in the segmented binary image equals the number of boundary or edge pixels, and the area of the potato was estimated as the total number of white pixels in the binary image *I(x,y)*. As shown in Fig. 1b, other parameters were also calculated such as the center of mass of a potato (centroid), the length as the major axis of inertia, the width as the minor axis of inertia and the angle of orientation of the tuber during its movement over the conveyor, which is expressed as the inclination angle of the major axis of inertia. Identifying the axes of inertia, coordinates of boundary points, centroid $(\bar{x}, \bar{y})$, inclination angle $(\theta)$ and major and minor axes in addition to extracting the boundary profile $r(t)$ from the boundary to the centroid are all illustrated in Fig. 1b.

### 2.2.4. Calculating shape parameters

*2.2.4.1. Size–shape parameters.* Conventional measurements of shape from size dependent measurements try to combine different size features such as area, perimeter, width and length together to form dimensionless expressions for shape description. There is a variety of simple geometric measures which were used to construct a representation of potatoes' shape. In this work, elongation, roundness, extent and eccentricity were measured which were then used in later statistical analysis to determine the shape of the potato. Equations used for calculating these geometrical parameters were described in detail by Du and Sun (2004) and Shouche et al. (2001).

*2.2.4.2. Fourier descriptors.* There are many techniques for the representation and description of the shape of objects. An important feature for the descriptors used to interpret the shape is that they must be invariant between images that are rotated, moved or scaled (Kim and Kim, 2000). Some methods extract a feature vector from the boundary to describe the shape which is commonly called the signature. The posterior analysis of these signatures allows obtaining an estimation of the shape. One of the most widely used techniques for shape analysis in biological products is the Fourier descriptor (FD). Zhang and Lu (2004) concluded that for general forms, the radius signature obtained from the distance of each point in the contour to the centroid, as used in this work, is the most suitable for deriving the Fourier descriptor.

In this work, from each segmented potato image, the boundary of each potato was first extracted from the two-dimensional image as illustrated in Fig. 1, and then the radius signature $r(t)$ as shown in Fig. 4 was obtained as the Euclidean distance between each boundary pixel $(x_t, y_t)$ and the centroid $(\bar{x}, \bar{y})$. The FFT algorithm required normalization of the resulting signature to a power of 2. Therefore, the one-dimensional boundary profile was linearly normalized to 512 equidistant points for equal level of comparison. This value was set empirically according to the size of the image but other values such as 128, 256 or 1024 were also tested with an identical result. This boundary signature was translated to the Fourier domain resulting in some Fourier descriptors. It was reported that only the low-order Fourier harmonic coefficients are adequate to characterize the shape information of the object which were considered as good candidates for shape descriptors.

As depicted in Fig. 4, there was a remarkable change in radius signature of the irregular potato with two secondary-grown tubers. The two secondary tubers caused a substantial change in the profile leading to extraordinary peaks in the signature compared to that of one of the regular-shaped potatoes. The radius signature of equivalent circle was also plotted in the same figure as a straight horizontal dash line to indicate that the polar signature is constant throughout its entire polar points. It is evident how the presence of two secondary tubers (bead-like tubers) seriously affects the boundary profile. To characterize the shape of all tested potatoes, the FFT of the normalized radius signature $r(t)$ was calculated by applying Eq. (1). Then the magnitude of the harmonic $h$ in the Fourier domain was calculated using Eq. (2) (Abdullah et al., 2006):

$$F(h) = \frac{1}{N}\sum_{t=1}^{N} r(t) \cdot \left[\cos\left(\frac{2\pi ht}{N}\right) - j\sin\left(\frac{2\pi ht}{N}\right)\right] \tag{1}$$

$$|F(h)| = \frac{1}{N}\sqrt{\left[\sum_{t=1}^{N} r(t)\cdot\cos\left(\frac{2\pi ht}{N}\right)\right]^2 + \left[\sum_{t=1}^{N} r(t)\cdot\sin\left(\frac{2\pi ht}{N}\right)\right]^2} \tag{2}$$

where $|F(h)|$ is the magnitude of harmonic $h$ in the Fourier domain, and $N$ is the number of points in the signature. The magnitude of boundary frequency change $r(t)$ in the spatial domain could then be represented by the magnitude of harmonic components in the Fourier domain $|F(h)|$. Eq. (2) produces a pattern which uniquely describes the shape of the potato. For validating shape extraction, the original boundary signature of a certain potato could be retrieved from the Fourier domain by using Eq. (3):

$$r(t) = \frac{1}{N}\sum_{h=1}^{N} F(h) \cdot e^{-j\frac{2\pi ht}{N}} \tag{3}$$

For effective shape information extraction, a method of harmonics multiplied by its magnitude $F(h) * h$ was used to effectively express the boundary profile of the potato. The $F(h) * h$ can be explained as the derivative of the boundary signature and $F(h) * h^2$ represents

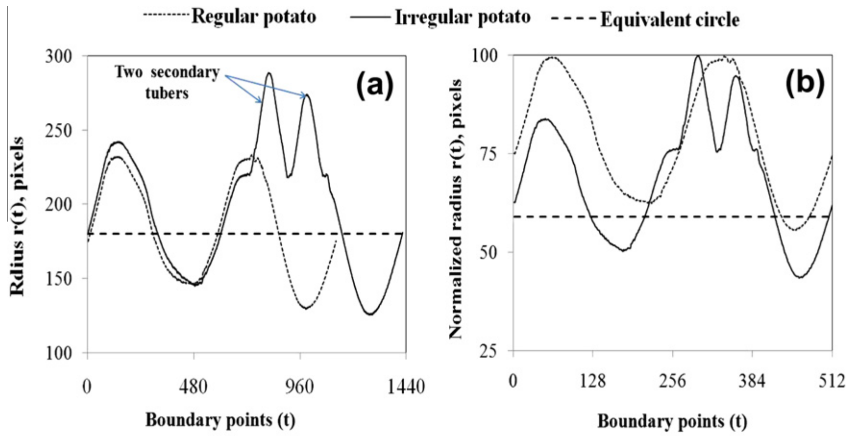


**Fig. 4.** Radius signature of the boundary points of a regular potato and an irregular potato with two secondary-grown tubers shown in Fig. 1 (a) Raw radius signature $r(t)$ calculated directly by Euclidean distance from the polar points to the centroid. (b) Radius signature is normalized to a max value of 100 and the number of polar points was normalized to 512 equidistant points to facilitate comparison. The radius signature of equivalent circle was also plotted as a straight horizontal dash line in both graphs to indicate that the polar signature is constant throughout its entire polar points. It is evident how the presence of two secondary tubers (bead-like tubers) seriously affects the boundary profile.

the curvature of the boundary and so on. Increasing the order of $h$ from 1 to 3 resulted in a significant enhancement of the higher frequency component to show the detailed noise in the boundary profile. Therefore, three parameters were calculated from Fourier expansion using the first 10 harmonics to describe potato shape as declared in Eqs. (4)–(6):

$$S_1 = \sum_{h=1}^{10} F(h) \cdot h \tag{4}$$

$$S_2 = \sum_{h=1}^{10} F(h) \cdot h^2 \tag{5}$$

$$S_3 = \sum_{h=1}^{10} F(h) \cdot h^3 \tag{6}$$

In addition, another parameter ($S_4$) was calculated as the percentage of $S_3$ from the total area of the potato as shown in Eq. (7):

$$S_4 = \left(\frac{S_3}{A}\right) \times 100 \tag{7}$$

The first harmonic of Fourier transform $F(0)$, corresponding to zero frequency, was considered as the average value of the radius signature $r(t)$. Also, the $F(2)$ harmonic could be considered as an expression of potato elongation (Tao et al., 1995). Only the low-order Fourier coefficients were required to characterize the basic shape of the object and were considered as good candidates for shape descriptors (Du and Sun, 2004). Therefore, only the first 10 coefficients were selected in this study for shape recognition and for calculating the Fourier-shape parameters ($S_1$, $S_2$, $S_3$ and $S_4$) that were finally used in the statistical analysis.

### 2.2.5. Selection of relevant shape features

The values of shape parameters calculated for the whole training dataset consisting of 228 images (190 regular and 38 irregular potatoes) were organized in a 2D matrix with 228 rows and eight shape features (columns) in addition to an extra one column vector of dummy-variable code [0,1] representing each potato's predefined shape class. In total, eight parameters were calculated as substantial candidates to describe potato shape: four size-dependent parameters (elongation, roundness, extent and eccentricity) and four Fourier-dependent parameters ($S_1$, $S_2$, $S_3$ and $S_4$).

Each tuber had its own parameters that were proportional to the tuber's characteristics and reflect its shape. Stepwise linear discriminant analysis was applied to identify the most effective parameters in characterizing potato shape. Stepwise discrimination was a standard procedure for variable selection, which based on the procedure of sequentially introducing the variables into the model one at a time. Hence, a model of discrimination was built step-by-step to evaluate all of these parameters to discriminate between the two classes of potatoes (regular and misshapen groups). Specifically, the values of each variable (eight shape parameters) were evaluated to determine which parameter(s) contributed most to the discrimination between the two groups. The number of variables retained in the final model was determined by the levels of significance assumed for inclusion and exclusion of variables from the model.

Prior to discriminant analysis, the data were first normalized by dividing on the standard deviation to be in the same scale. Also, to validate the analysis, full cross validation by leave-one-out method approach was implemented during development of the discriminant analysis model in which one sample was preserved for validation and the rest of the samples were employed to build the discriminant analysis calibration model which was then used. The same routine was repeated until each sample was used once as a validation sample. This method of variable selection was operated in an iterative manner for systematically removing shape parameters whose $F$-statistics are smaller than $F$-to-remove, and, retaining those parameters whose $F$-statistics are greater than $F$-to-enter values. For this analysis, a level of significance of $\alpha = 0.05$ was applied and a threshold $F$-value of 0.15 was used both for inclusion and excluding parameters from the model.

### 2.2.6. Grading regular potatoes by size

Once the shape category was identified, the misshapen potatoes were isolated in a separate class; meanwhile the regular potatoes were graded to different grades based on their size. For regular potatoes, the developed grading algorithm depended on estimating the average area of the tuber during its movements throughout the camera's field of view by calculating all white pixels in the binary images and then giving an average value for all views. Based on the grading standards required by quality control authorities or the requirements of national or international markets, certain thresholds could be easily adjusted to fulfill these requirements. In this study three thresholds were supplied to the algorithm to segregate four different size grades namely small, medium, large and extra large grades (i.e. $<40$ cm$^2$, 40–55 cm$^2$, 55–70 cm$^2$ and $>70$ cm$^2$ respectively). The grade of a potato was assigned if it fell within the limits of these thresholds. The potatoes were pre-classified to these particular sizes and the result of grading was evaluated. An optimum classification can be guaranteed provided that the threshold values were correctly chosen.

## 3. Results and discussion

### 3.1. Shape parameters

The average and standard deviation values of all shape parameters extracted from database images of the training set (190 regular and 38 misshapen potatoes) are shown in Table 1. The results revealed that the misshapen potatoes had a wide range of variation for all shape parameters compared to the regular ones. This was clear by looking at the values of standard deviation for misshapen groups which were quite higher for all shape parameters.

### 3.2. Fourier analysis

Shape detection algorithm depended on calculating both size-dependent and Fourier-dependent shape features. Fourier transform was used to characterize the changes in the polar signature in the spatial domain $r(t)$. The calculated magnitudes of Fourier transform depend basically on these polar signatures extracted from potato's boundary pixels. In essence, Fourier transform was basically used to reduce the dimensionality of the edge points from its spatial domain to a new frequency domain. The higher harmonics of Fourier transform carry different shape information which could be used to explain the irregularity of the tubers. Therefore, the magnitude of Fourier expansion $|F(h)|$ at different harmonic components calculated using Eq. (2) of regular and misshapen potatoes indicated that the misshapen potatoes showed high values of $|F(h)|$ compared to those of regular-shaped potatoes.

### 3.3. Selecting effective shape parameters by stepwise discriminant analysis

Stepwise discriminant analysis was applied to identify a subset of dominant shape features (Elongation, Roundness, Extent, Eccentricity, $S_1$, $S_2$, $S_3$, or $S_4$) that most distinguish potato shape groups. The summary of shape variable selection by stepwise discriminant analysis is presented in Table 2. At the beginning of the test, all eight shape parameters were involved in the model, and in every step one parameter (variable) was removed according to its Wilks' Lambda and $p$-value. The variable that did not contribute significantly in discriminating the two shape classes was removed from the model. It was obvious from Table 2 that the discriminant model kept only six parameters (roundness, extent, $S_1$, $S_2$, $S_3$ and $S_4$) and removed both elongation and eccentricity from the final model. This means that two size–shape parameters in addition to four Fourier-shape parameters were very effective in distinguishing the shape of tested potatoes ($p < 0.0001$).

In addition, Table 3 showed the classification obtained using the developed discriminant analysis model for the training set. The selected six shape parameters were able to predict potato shape with an overall success rate of 96.5%. Regular tubers were predicted with a 100% success rate; while the accuracy of predicting misshapen tubers was 79%.

After identifying the most important shape parameters for characterizing potato shapes and testing their performance for shape detection, the discriminant analysis model created classification functions which minimize the possibility of misclassifying cases into their respective groups or categories. To differentiate between the two groups, two classification functions were produced by the discriminant analysis model to describe each group. The ultimate aim of discriminant analysis was to unambiguously determine the identity of each tuber in terms of its shape. The well-defined discriminant analysis learns to recognize the class of the tuber based entirely on the selected important shape parameters without any other information than the logical grouping of the tubers. The resulting discriminant function was then applied to each tested tuber and a decision was made as to which shape category the tuber belonged to Table 4 presents the extracted classification functions. For instance the linear equation for regular tuber should be written as Eq. (8). Once the model was built and the discriminant functions were derived, linear discriminant equations were then formulated to be used in predicting the shape of unknown potatoes.

**Table 1**
Shape parameters (mean ± standard deviation) of regular and misshapen potatoes.

| | Shape parameter | Regular | Misshapen |
|---|---|---|---|
| Size–shape parameters | Roundness | 0.98 ± 0.08 | 0.79 ± 0.14 |
| | Elongation | 0.598 ± 0.10 | 0.597 ± 0.16 |
| | Eccentricity | 2.42 ± 2.02 | 2.18 ± 1.81 |
| | Extent | 0.80 ± 0.02 | 0.74 ± 0.05 |
| Fourier-shape parameters | $S_1$ | 683.26 ± 127.91 | 652.62 ± 314.41 |
| | $S_2$ | 3324.43 ± 677.03 | 3353.24 ± 1805.12 |
| | $S_3$ | 21939.07 ± 4850.8 | 22702.30 ± 13175.9 |
| | $S_4$ | 25.08 ± 5.73 | 25.27 ± 13.99 |

**Table 3**
Confusion matrix of discriminant analysis model with leave-one out cross validation to predict the shape of training set potatoes.

| From/to | Regular | Misshapen | Total | % correct |
|---|---|---|---|---|
| Regular | 190 | 0 | 190 | 100.0 |
| Misshapen | 8 | 30 | 38 | 79.0 |
| Total | 198 | 30 | 228 | 96.5 |

**Table 4**
Classification functions derived from discriminant analysis model for predicting potato shapes.

| Shape parameter | Regular | Misshapen |
|---|---|---|
| Intercept | −73.396 | −35.560 |
| Roundness | 82.469 | 51.275 |
| Extent | 53.328 | 38.452 |
| $S_1$ | 337.996 | 166.552 |
| $S_2$ | −427.970 | −182.302 |
| $S_3$ | 115.076 | 37.311 |
| $S_4$ | 71.767 | 42.855 |

**Table 2**
Summary of shape parameter selection by discriminant analysis.

| No. of variables | Variables | Variable in/out | Status | $P$ < Lambda | F |
|---|---|---|---|---|---|
| 8 | Elongation, Roundness, Extent, Eccentricity, $S_1$, $S_2$, $S_3$, and $S_4$ | | | | |
| 7 | Roundness, Extent, Eccentricity, $S_1$, $S_2$, $S_3$, and $S_4$ | Eccentricity | Out | 0.0001 | 0.142 |
| 6 | Roundness, Extent, $S_1$, $S_2$, $S_3$, and $S_4$ | Elongation | Out | 0.0001 | 1.683 |

$$\text{Regular class} = -73.396 + 82.469 \times \text{Roundness} + 53.328 \times \text{Extent} + 337.996 \times S_1 - 427.970 \times S_2 + 115.076 \times S_3 + 71.767 \times S_4 \tag{8}$$

Hence, these final linear equations were then supplied into the developed algorithm as the corner stone to predict the potato shape class during the real-time operations. The obtained linear discriminant equations from the analysis were implemented in the classification algorithm to predict the shape of another randomly-selected set of samples consisting of 182 tubers (162 regular and 20 misshapen potatoes) to realize the overall performance of the prototype for classifying potatoes during in-line operations. During on-line implementation, the image (view of one side of the potato surface) was not accounted until the entire perimeter of such view appeared in the camera's field of view, then its features were extracted and the discriminant equations were applied in the real-time to identify its shape class. Fig. 5 depicts one tuber during its movement on the conveyor belt at four different side positions. This tuber exhibited regular shape in two views (the second and fourth views) and exhibited irregular shape in the other two views (the first and third views). Due to the irregularity in its boundary, the boundary signature displayed some distortion compared to the regular view. This odd distortion is then interpreted by shape features as a misshapen potato. Therefore, the algorithm classified this tuber as a misshapen class since it presented one or more irregular shapes.

The results presented in Table 5 show the performance of the developed image processing algorithms depending on the discriminant analysis for detecting misshapen potatoes when they were conveyed by the machine vision system at a speed of 1 m/s in the validation experiment. The accuracy of the system was reasonable, being capable of detecting 75% of all misshapen potatoes and correctly classifying 98.8% of the regular potatoes, confirming that integration between size–shape parameters as well as Fourier-shape parameters were efficient in shape classification.

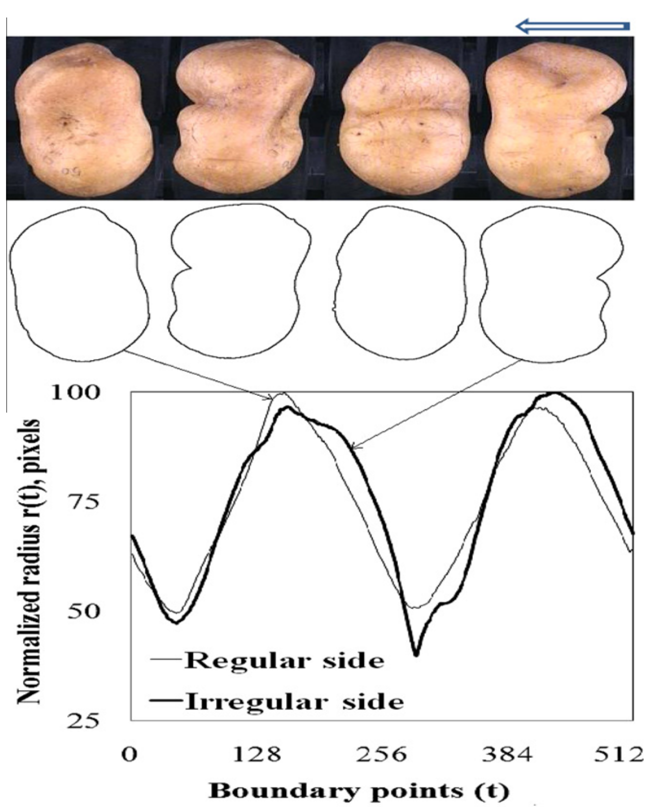


**Fig. 5.** Extraction of potato shape during its movement on the conveyor belt. Irregular views present a distortion in the boundary signature $r(t)$. The arrow on the top of the figure indicates the direction of movement.

**Table 5**
Classification accuracy of the image processing algorithm in in-line operation for sorting shape in testing set.

| Real/estimated | Regular | Misshapen |
|---|---|---|
| Regular | 98.8 | 1.2 |
| Misshapen | 25.0 | 75.0 |

**Table 6**
Confusion matrix of grading process in on-line operation. The misshapen potatoes (20 tubers) were defined in a separate class and the regular potatoes (162 tubers) were graded according to pre-defined thresholds.

| From/To | Grade I | Grade II | Grade III | Grade IV | % Correct |
|---|---|---|---|---|---|
| Grade I | 45 | 0 | 0 | 0 | 100 |
| Grade II | 0 | 60 | 0 | 0 | 100 |
| Grade III | 0 | 0 | 35 | 0 | 100 |
| Grade IV | 0 | 0 | 0 | 22 | 100 |

Although the regular tubers were efficiently identified in the training and validation stages, there was a low classification performance in the case of the misshapen tubers. However, compared to some studies in shape detection in potatoes (Tao et al., 1995) who achieved 89% of accuracy in detecting the regularity of potatoes, the detection performance of the developed machine vision system was reasonably acceptable if we consider that this result was obtained by an automatic system working in real-time operation. In our study, the total processing time needed by the machine vision system using the hardware described was 45 ms ordered as 17, 4, 2, 9, 13 ms for segmentation, median filtering, boundary extraction, feature extraction and data presentation respectively. This time excludes the image acquisition (40 ms) since it was performed concurrently with the processing of the previous image.

### 3.4. Grading regular potatoes by size

By estimating the number of tubers within each pre-classified size grades (small, medium, large and extra large grades); the system offered 100% accuracy for providing such grades as shown in the confusion matrix presented in Table 6 for the validation set (162 regular tubers). The developed software is very friendly to the user if the operator needs to change the grading thresholds which are imperative requirements of the industry. Furthermore, if a linear relationship could be established between potato sizes and weights, it could be supplied to the algorithms to grade potatoes based on their weight.

## 4. Conclusions

As a part of a whole machine-vision system, an image processing technique was developed and elaborated to classify potatoes based on shape analysis. The experimental machine vision system was designed and constructed to test the image processing algorithms' ability to detect misshapen potatoes. Algorithms were developed to acquire and process images of potatoes in real time while they travel over a high speed conveyor belt. Stepwise linear discriminant analysis was used to determine which shape parameters were most responsible for detecting misshapen potatoes. Roundness and extent as size–shape parameters in addition to other four parameters calculated from Fourier expansion of the polar signatures of potato boundary were found to be effective in describing potato shapes. The in-line evaluation of the proposed system showed that the overall accuracy of the system for detecting potato shape was 96%. In briefed, it could be concluded that integration between size–shape parameters and Fourier-shape parameters were very efficient in shape classification. However, before nominating this study in a real industrial application, some modifications are advisable in order to enhance the system so that it has the ability to detect other features such as defects, bruises, cuts, diseases, sprouts and greening.

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