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Defect detection in eggshell using a vision system to ensure the incubation in poultry production

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ABSTRACT

This paper describes a method for detecting defects on curved surfaces. In particular, this research focuses on defects in poultry eggs for damage identification in the shell as a result of thin-shelled eggs. The vision system is based on defect detection by scanning a laser pattern of structured light and imaging, highlighting the changes in geometry as a result of deformation of the laser transitions generated by scanning the egg surface. Then, the images are analyzed to obtain equidistant points along the curve and evaluated by creating a cubic spline interpolation. The interpolation allows for the extraction of descriptive metric characteristics to observe the disparity between curves, illustrating the defects by performing graph interposition. The obtained metric information is used to classify the defective samples by developing an algorithm using an artificial neural network, trained with a database composed of 200 images, wich achieves 97.5% efficiency during the evaluation of 150 egg samples. This technique can be applied to detecting corrugated, wrinkled, pimpled, odd- shaped and misshapen eggs.

1. Introducción

The necessity of achieving superior food quality makes the inspection of its defects of highly important during production processes [1]. Food product defects are one of the inspection characteristics that have originated from researchers focusing on detecting defects using computer vision and artificial intelligence techniques. Specifically, in the poultry industry, eggshell defects affect quality and production. As a result, industrial incubators obtain a low fecundity percentage. The most prominent defects are eggs without shells on the integral membrane, or with fragile shells. These incidences vary by approximately 0.5 to 6%, and 12 to 15% eggs are clasified as not feasible for incubation. The defects are mainly owing to an immature or defective uterus, produced by laying hens prematurely, thereby resulting in eggs with incomplete calcification [2]. The external defects are consequences of inner modifications, and these can be studied by techniques involving the echographic method [3]. Taking into account the abovementioned problems, egg quality assessment methods regarding defects related to their shape have been evolving, as the use of manual inspection by human personnel may be affected by various physiological aspects such as visual fatigue, in addition to involving a high degree of subjectivity in the product quality determination. The evolution of opto-mechatronic system development is mentioned in this paper to demonstrate its contribution to detecting particular egg defects, taking into consideration mechanical techniques, spectroscopic principles, and computer vision [4].

Patel et al. proposed a neural network model capable of differentiating eggs with a particular defect from those without imperfections by using computer vision and robust neural network models to minimized sensitivity in eggs from different sources [5].

Nakano et al. developed a device for the non-destructive detection of eggs with cracked shells and leaking cracks, that are unclean, and with blood spots, by incorporating color and monochrome charge coupled device (CCD) cameras [6].

Mertens et al. proposed a design for an offline computer vision system to differentiate and quantify the presence of different dirt stains on brown eggs, such as dark (feces), white (uric acid), blood, and yolk stains. The system provided uniform light exposure around the egg, and images of dirty and clean eggs were captured, stored, and analyzed [7].

Another author proposed the measurement of the internal quality in chicken eggs by using visible transmittance spectroscopy technology. In this case, the potential of the ultraviolet and visible (UV/VIS 200–800 nm) transmittance method used to inspect the internal quality (freshness) of intact chicken egg was investigated [8].

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Moreover, Deng et al. proposed a detection methodology for eggshell cracks, using continuous wavelet transform and a support vector machine (SVM) technique consisting of an experimental system and a data processing system [9].

Another method presented algorithms based on image processing for detecting internal blood spots and dirty eggshells, from eggs under different illuminations, to carry out image processing and extraction of useful features of captured eggs images by means of machine vision, for which Dehrouyeh et al. developed an algorithm in HSI (Hue Saturation Intensity) color space [10].

Xiong proposed a novel method based on acoustic features and an SVM. A sound signal acquisition system was designed based on a microcontroller; the power spectra were received for high-quality shell eggs and cracked eggs [11].

An algorithm was developed based on Fuzzy thresholding and the SUSAN edge detector to identify and eliminate cracked eggs quickly and precisely in the poultry process of manufacture. The technique provided a nondestructive testing system using digital image processing (DIP) with an efficient algorithm [12].

An egg system vacuum chamber under pressure was fabricated to force open the eggshell micro-crack, and a machine vision system was developed to obtain the image. A robust algorithm was designed to extract the micro-crack from the image without being affected by the presence of dirt in the eggshell [13].

Ibrahim et al. investigated the egg grade classification and dirt inspection system using a combination of image processing techniques, focusing mainly on the egg grade classification algorithm and dirt inspection process [14].

Another design used an intelligent system based on combined fuzzy logic and machine vision techniques for egg grading, using parameters such as egg defects and sizes. The detected errors were internal blood spots, cracks, and eggshell breakages [15].

Soltani et al. proposed an egg qualifying system based on dielectric technology within the radio frequency range, with machine vision and artificial neural network techniques. The vision system was used to compute the volume as well as major and minor diameters of the eggshell, and a dielectric sensor was applied to measure the gain and phase shift voltages related to the egg loss factor and dielectric constant [16].

Soltani and Omid proposed research on the possibility of the nondestructive classification and quality inspection of eggs using a dielectric detection technique within the radio frequency range. Thereby, several machine learning techniques were developed for freshness detection, including artificial neural networks (ANNs), Bayesian networks, decision trees and SVMs [17].

Moreover, visible radiation technology is increasingly being used for the inspection of eggshell cracks. In this case, a novel technique based on Radon transform was developed for feature extraction, while the classification was established by means of a multiclass SVM. The experimental results indicated that the proposed framework performs effectively on eggs from the same or different poultry houses in temrs of sensitivity and specificity [18].

A further technique for egg crack detection was designed and implemented using a machine vision system based on a modified pressure chamber and continuously rotating egg. The proposed method successfully collected surface images of the entire egg using only one pressure modification, which reduced the operation time and risk of enlarged cracks [19].

Automated systems based on artificial intelligence and computer vision techniques allow for the existence of production line monitoring systems in the poultry industry. In this work, we present a new vision system for detecting defects in curved surfaces such as an eggshell. The system is based on optical metrology and artificial intelligence, which is a nondestructive technique as it uses structured light originating from a laser and projected onto the eggshell. The method permits to obtain images on the structured light scanning over the entire eggshell surface, which were compared with the training images selected for the ANN. The defect identification was conducted by obtaining points distributed in the curvature of an image, and cubic spline interpolation was performed, which was used as input for a neural network in order to classify the analyzed samples. The optimal result was obtained by using a cubic spline with five points, with an efficiency of 97.5%.

2. Experimental setup

Fig. 1 illustrates the vision system used for the detection of eggshell defects. It consists of a CCD detector model DFK31 BF03 FireWire 400 industrial color camera, with a sensitivity 0.15 l×, a resolution of 1024×768, and a 30-fps frame rate shutter 1/10,000 to 30 s, equipped with a lens of 38 mm focal length, located at a distance of 200 mm from the sample to be analyzed. A Line laser diode Adafruit, ID: 1057, class IIIa, with a center wavelength of 650 nm, was used to project the structured light onto the eggshell. The optical power of the laser was 5 mW and the numerical aperture was 120° from a distance of 150 mm, ensuring illumination conditions of approximately 1 l× in order to capture the image without saturation on the camera. Structured laser light scanning (3 mm wide) was performed on the entire eggshell surface, obtaining 20 images per sample with an acquisition speed of 4 fps. A total of 200 egg samples were selected by means of visual classification to divide the samples into two groups. The first group of 100 samples consisted of eggs without defects; that is, with no damage presented in their structure and surface. The second group of 100 samples consisted of eggs (with structure and eggshell surface defects) that presented defects in their structure and eggshell surface. If the evaluated egg sample presented defects, this projected laser pattern was deformed, generating a non-uniform curvature, thereby highlighting possible

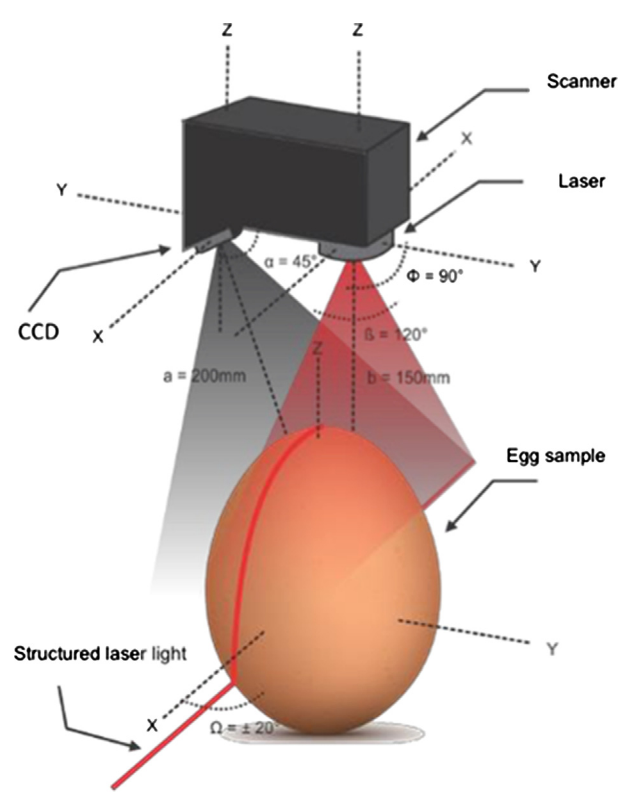

Fig. 1. Schematic diagram of vision system.

imperfections in the egg, as illustrated in Fig. 2. The defect was captured by an image from the CCD camera and processed by the pre-processing stage to provide a defect degree. The digital images captured by the optical system were compared in .jpg format and prepared with Matlab® (MathWorks, Inc., USA) using a Hewlett Packard Pavilion dm4 laptop (Windows® 7 Professional, Intel® CoreTM i5, 8 GB, Intel® HD, Graphics 3000, HD 500 GB).

Fig. 3 illustrates the ANN proposed for realizing the classification process of the analyzed samples. For the three neurons in the input layer, the results obtained from Eqs. (2)–(4) were introduced into an activation function of the logsig type, while two neurons in the hidden layer were activated by a logsig function, and one neuron in the output layer were activated with a purelin type function.

The linear length measured in pixels of the exact curvature was determined by the sum of distances between the set points defining the curve, concerning its location on the axis of the ordinates (1):

$$L1 = \sum_{i=1}^{k} \left| \left(yr^{(i)} - yr^{(i-1)} \right) \right| \tag{1}$$

where L1 is the linear length, and (i) is the point matrix of the real real curvature obtained from an image.

The linear length in pixels of the interpolated curvature by means of cubic spline was determined by the sum of the distances in pixels between the set of points defining the curve, concerning its location on the axis of the ordinates (2):

$$L2 = \sum_{i=1}^{k} \left| \left(ys^{(i)} - ys^{(i-1)} \right) \right| \tag{2}$$

where L2 is the linear length, (i) is the point matrix obtained from a real curvature using the interpolated curvature.

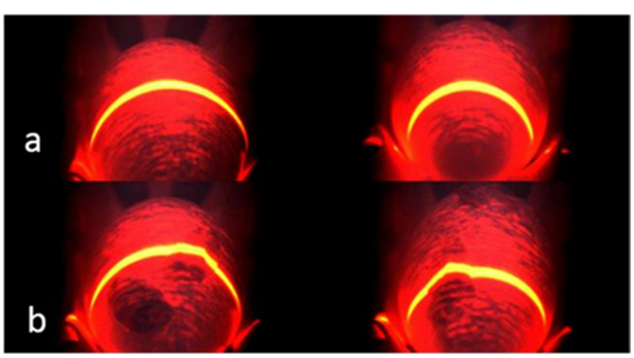

Fig. 2. Structured light projected onto the egg: a) without defects, b) with defects.

The area in pixels between the two curves when a graphical interposition of the real and interpolated curve was determined by the sum of the differences between the distances of the set points defining both curves, concerning their location on the axis of the ordinates (3):

$$A = \sum_{i=1}^{k} \left| \left(ys^{(i)} - yr^{(i)} \right) \right| \tag{3}$$

where A is the area.

3. Image processing stage

A Matlab function for identifying eggshell defect was performed, which consisted of four steps: a) image pre-processing, for conditioning and filtering of the parameters of interest, to be described in section 3.3; b) image analysis, which consists of obtaining precise structured light points in order to apply cubic spline interpolation, and generates a normal approximation of the egg curvature; c) characteristics extraction, for obtaining the parameters that describe the differences between the real and interpolated curvatures to obtain values that indicate the disparity of the curved forms; and d) defect detection and classification using the ANN.

3.1. Preprocessing

Fig. 4 shows the images of the curvature of an egg without defects. It can be observed that the structured light from the laser is projected using the geometry with a smooth and defined curve.

Fig. 5 illustrates each of the steps involved in the image preprocessing. Fig. 5a presents the effect caused by the structured light projected onto the eggshell. The curve exhibits deformed projections that define and emphasize the zones in which the defects are present. With these images, it was possible to obtain sufficient information to perform a comparative analysis, evaluating the image curves and thereby determining their continuity and uniformity. The scattering was removed under controlled lighting conditions, and with the camera shutter set a clear image was obtained (Fig. 5b). The preprocessing was focused on the region of interest to

Fig. 4. Structured light projected in eggshell without defects.

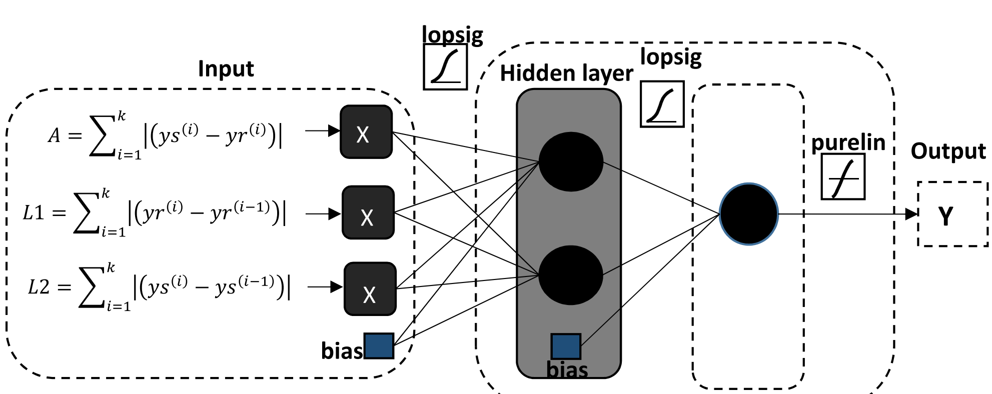

Fig. 3. Artificial neural network Proposed.

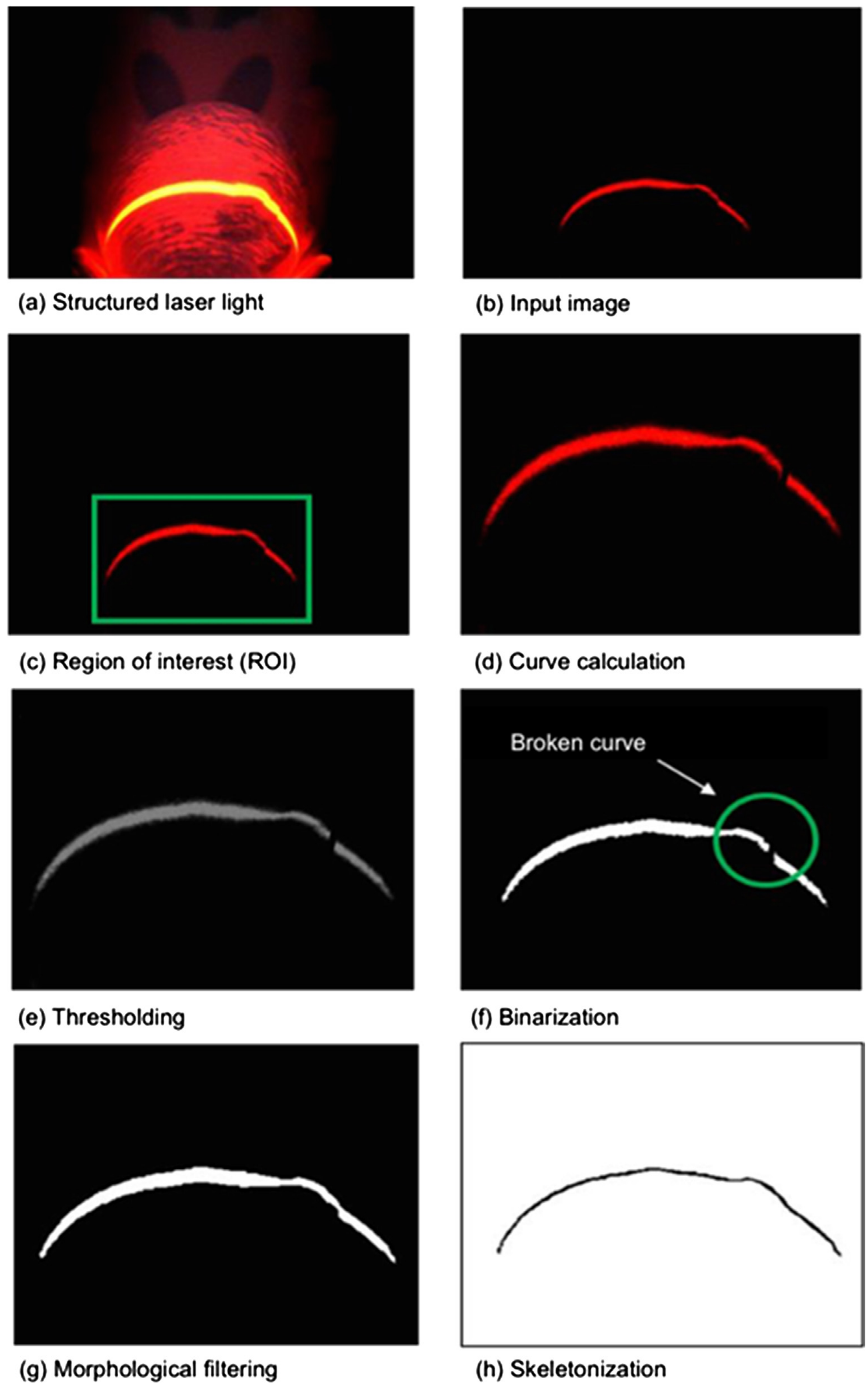

Fig. 5. Image preprocessing obtained from the structured light projected onto eggshell.

reduce the image pixel numbers. Fig. 5c illustrates the area of interest identified by the preprocessing stage from Fig. 5b. Fig. 5d indicates the new image cut to the dimensions of the box marked in Fig. 5c, as it contains the zone in which the curvature recorded by the laser projection is located, which it is analyzed at a later stage. It should be noted that the computer vision operates with a binary image to realize segmentation by image intensity to generate reconstruction algorithms or recognize structures. The most common means of creating binary images is by using the threshold value of a grayscale image; that is, a limit value (or an interval) is selected to take into account the fact that higher intensities will be coded as 1, whereas those below will be coded as 0, thereby obtaining an optimal threshold and binarization that is appropriate to the image. Fig. 5e and f illustrate the results obtained after applying a limit adjustment and the binary representation of the analyzed image, respectively. However, as the noise is unwanted information that degrades the image, a filter was applied to eliminate any scattered spots in the image that were not removed when the camera shutter was set. As a result of applying the filter and the initial curve characteristics from the projection of the structured light onto the eggshell surface, the projection curvature line presented a discontinuous section. Therefore, it was necessary to complete the curve line, as can be observed in the image marked in Fig. 5f. This was solved by applying a morphological operation known as closure that is carried out by applying a dilation followed by an erosion, as well as by using the same structural element in both actions, to compensate for the possible absence of image pixels to obtain a well-defined curvature, retaining the main object characteristics, as can be observed in Fig. 5g. Finally, Fig. 5h illustrates a skeletonization of the image, which consists of obtaining a continuous pattern containing the least amount of data possible while maintaining a minimum trace of the original object.

3.2. Image analysis

Certain images illustrate the curvatures highlighted by the laser structured light pattern. Thus, it was necessary to use a mathematical method that obtains points from the recorded curve graph and draw a new smoothed curve that describes the uniform shape of the egg curvature, as it is difficult to analyze numerical data without a defined sequence.

In this case, segmental cubic interpolation was used, as this type of polynomial presents four constants that ensure a smooth union between the segments forming the curve, avoiding possible oscillations between each pair of data points allowing for continuity at the interval ends. The cubic spline used was presented by Burden (1991) in Eq. (4):

$$S_i(x) = \propto_i + \beta_i(x - x_i) + x_i(x - x_i)^2 + \delta_i(x - x_i)^3 \quad (4)$$

where S_i (x) is the cubic function for a segment, x_i is the firs point of the segment (I = 1, 2, n), x is the point of evaluation of the function, ∝_i, β_i, x_i, δ_i are function coefficients.

Fig. 6a illustrates the graph corresponding to a curve obtained by the image pre-processing (inverted image from Fig. 4h) of a deformed eggshell, whereas Fig. 6b presents the graph obtained from Fig. 6a after applying cubic spline interpolation with five equidistant coordinate points selected in the image. A well-defined and smoothed curve was collected for comparison with an eggshell without defects.

3.3. Characteristic extraction

Fig. 7 illustrates a comparison of both graphs of Fig. 6a and b. An evident disparity can be observed between the two charts, which makes is possible to visualize the case when the eggshell does not present defects.

Taking into account the extraction characteristics makes it possible to reduce the processing computing time, using the definition of the curve structures and the relationships that are presented in the interpolation.

4. Results and discussion

The characteristics defining the analyzed curvatures must be interpreted to determine whether samples are geometrically uniform. The use of a neural network was considered as an artificial intelligence technique to perform classification of the samples, based on the characteristics extracted from the images and obtaining an output that specifies whether or not defects exist. An algorithm was developed using Matlab® (MathWorks, Inc., USA) base don an ANN of th Levenberg-Marquardt back-propagation type, and offline training was performed with a group composed of 200 images. Fig. 8 illustrates only eight images, four in which the eggshell presented defects, to obtain a similar output.

Analysis and interpretation of the acquired information were achieved by using the image processing and ANN as a classifier.

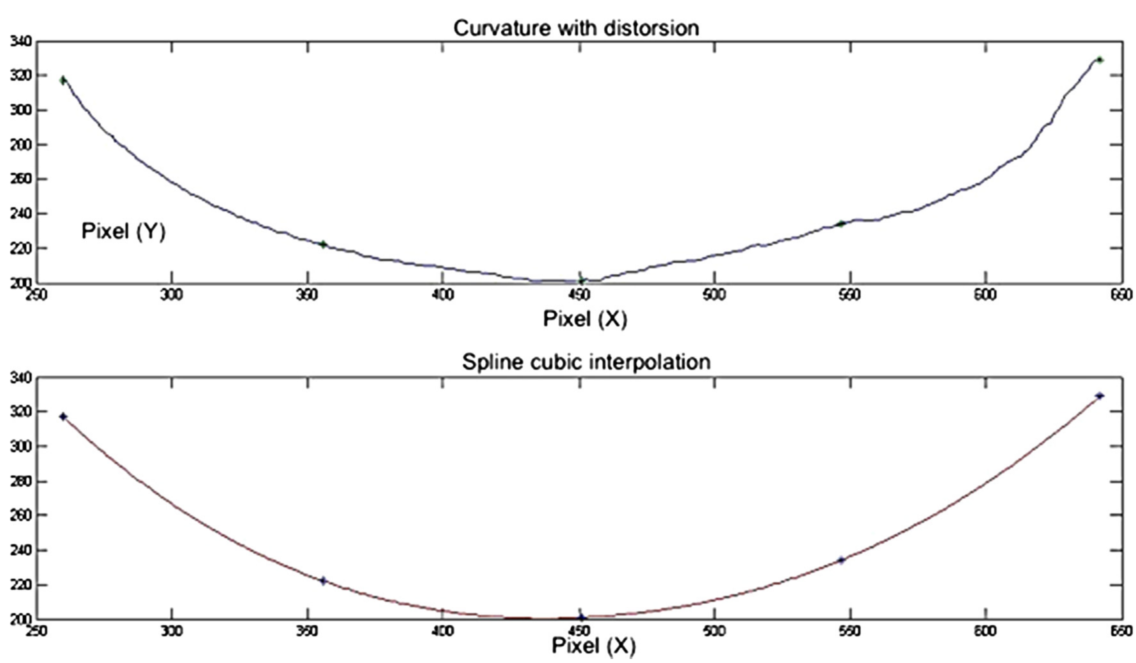

Fig. 6. a) Representation of graph in pixels of deformed curve; b) curve obtained after applying cubic spline.

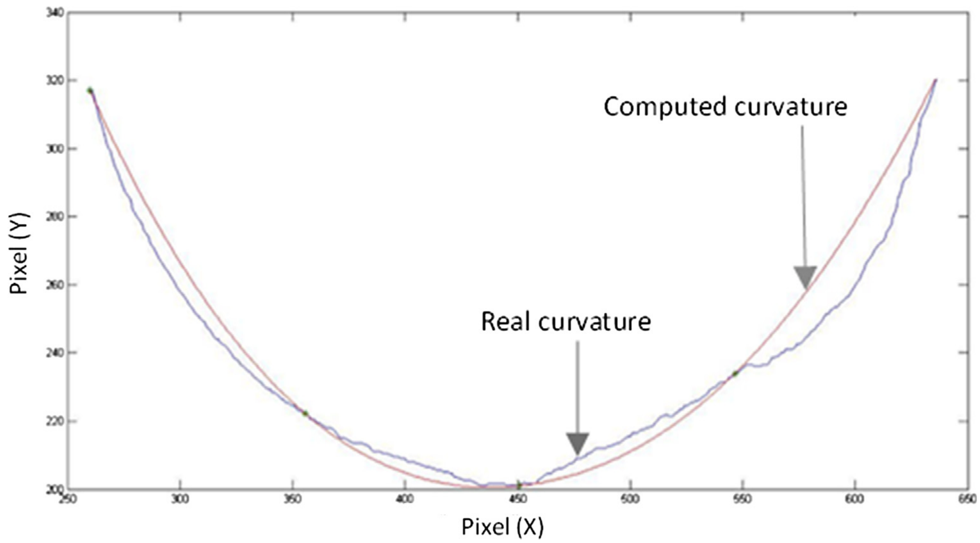

Fig. 7. Interposed curves of Fig. 6.

Fig. 8. Image database: a) Samples without defects; b) Samples with defects.

Tests were performed with four, five and six points in the cubic spline to observe the generated variations in the behavior of the algorithms to obtain the optimum operation point at which the highest algorithm efficiency was recorded, achieving the lowest mean square error (MSE). The number of image samples considered for carryig out the detection was 200, and the training images for the ANN input were varied among 50, 100 and 150.

The time processing obtained for the computing to detect the defects was a constant 250 ms in all tests. Table 1 displays the results obtained from the performed tests. The established variations were defined as a function of the number of points taken for the cubic spline interpolation, as well as the sample and training images. The minimum efficiency obtained using the proposed method was 91.5%, taking four points on the cubic spline and

Table 1
Results obtained from realized samples.

Tests	Training images	Detections	Errors	Epoch	MSE	Efficiency (%)
CUBIC SPLINE: 4 POINTS						
1	50	183	17	39	8.24E-06	91.50
2	100	187	13	80	8.44E-06	93.50
3	150	194	6	134	7.11E-06	97.00
CUBIC SPLINE: 5 POINTS						
1	50	184	16	10	8.15E-06	92.00
2	100	187	13	33	8.60E-06	93.50
3	150	195	5	61	2.60E-06	97.50
CUBIC SPLINE: 6 POINTS						
1	50	190	10	19	5.15E-06	95.00
2	100	191	9	17	7.27E-07	95.50
3	150	193	7	347	8.62E-06	96.50

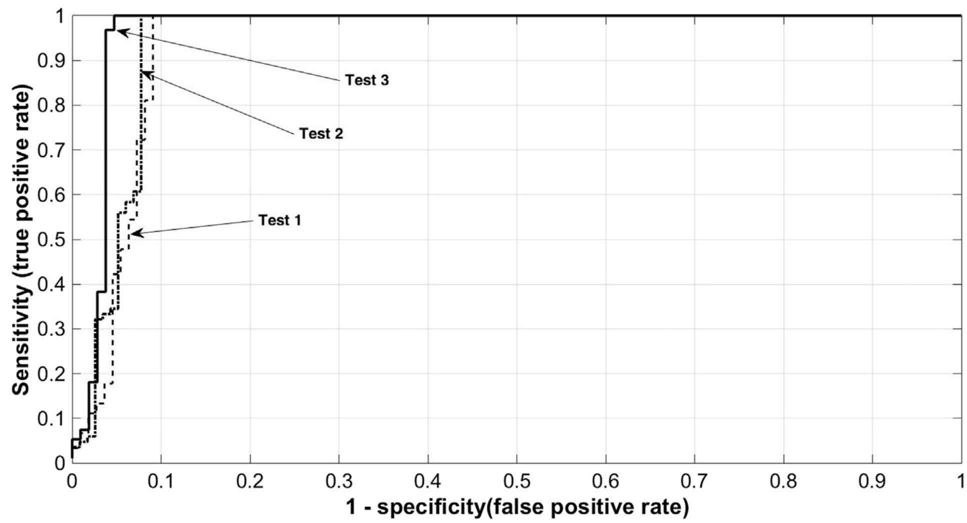

Fig. 9. ROC curve comparison results for tests under 50, 100 and 150 (Test 1, 2 y 3, respectively)) training sets for neural network as a classifier for eggshell defects.

detecting 183 eggshells with 200 defects. When the cubic spline with six points was used, the efficiency was higher than 95% increasing by 0.5% as a function of the number of training images. The highest efficiency achieved was 97% using the cubic spline with four and five points and with 150 training images. The dependency of the efficiency and the number of detections was linear with a rate of 0.51289% per etection. It should be mentioned that the eggs were randomly placed and the system could detect eggshells including with and without defects. The error column describes the amount of eggs that the system could not differentiate as defective or non-defective. In this manner, the system detect both, always considering 200 images, of which half were with defects. Therefore, taking into account the amount of eggs detected and the error column, a total of 200 eggs were obtained. It can be observed that most authors have focused on the detection of eggshell breakage and dirt, among others and have used different detection techniques. Nobody has yet proposed defect detection with reference to the eggshell curve However, the efficiency obtained using our proposal is highest compared to other techniques. The laser as an optical source offers a well-defined curve projected onto the eggshell, which is very important for the CCD camera to obtain a quality image

Fig. 9 illustrates the receiver operation characteristic (ROC) curves using the variable area A in pixels (Eq. (3)) as the parameter cut-off for the discriminator system in the detection of eggshell defects by means of the ANN classifier. This parameter was taken into account owing to its implicit relationship with L1 and L2 linear length in pixels (Eqs. (1) and (2)).

Taking inot account the area under the ROC, these results demonstrate that test 3 was most efficient, as it exhibited major discriminative ability. This is corroborated by the areas under the ROC curve, which were 0.8907, 0.9018 and 0.9370 corresponding to tests 1, 2 and 3, respectively.

5. Conclusion

The results indicate that the proposed vision system could identify defects on curved surfaces, such as those found in poultry eggs. The highest detection efficiency was 97.5% with an MSE of $2.60X10^{-6}$ and a processing time of 250 ms, obtained using 200 test images and 150 training images with Levenberg-Marquardt ANN backpropagation. There is a strong dependence on the algorithm efficiency concerning the number of points used for interpolation, as a decrease in the number of points generates variations of agreement between the analyzed curves, despite no noticeable variations being observed. It is important to mention that an increase im interpolation points causes the cubic polynomials formed to adapt more closely to the real curve, resulting in essential defects being omitted in samples with alterations in their geometry. Therefore, the most superior result achieved was located as a function of a cubic spline representation of five points. Following the same procedure illustrated, the vision system can be adapted for detection for any known defects in eggshells, as corrugated, wrinkled, pimpled, odd-shaped and misshapen eggs.

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