Digital Image-based Inductive Characterization and Classification to Improve the Quality Inspection of Diverse Food Products

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Abstract. With the increasingly demanding international regulations for import and export of food products, as well as with the increased awareness and sophistication of consumers, the food industry needs accurate, fast and efficient quality inspection means. Each producer seeks to ensure that their products satisfy all consumer's expectations and that the appropriate quality level of each product is offered and sold to each different socio-economic consumer group. This paper presents three study cases where digital image analysis and inductive characterization techniques have been successfully applied to improve the quality inspection process. Three very different and unrelated basic food products are studied: Hass Avocado, Manila Mango and Corn Tortillas. Each one of these products has some special and particular features that complicate the quality inspection process, but each of these products is also very important in economical terms for the sheer volume of their production and marketing. Experimental results of each case shows that the general technique has great accuracy and significantly lower costs.

Keywords: Inductive characterization, digital image analysis, corn tortilla, hass avocado, manila mango, boundstar.

1 Introduction

Nowadays, assessing the quality of food products involves mostly using physical methods. These methods can be non-destructive (produce compression, tactile testing) and destructives (penetrometers); however, even traditional non-destructive methods may represent a quality dropping, because the produce is usually delicate and can be easily damaged (Ochoa et al., 2009). For this reason, newer noninvasive techniques have been proposed. Noninvasive methods such as acoustic, spectroscopic, and digital image analysis, including multi- and hyperspectral imaging techniques, have been widely applied to evaluate the quality foods. However, acoustic and spectroscopic methods (near-infrared, nuclear magnetic resonance, and magnetic resonance imaging) could be relatively expensive and laborious, and a large number of samples, as well as a large laboratory area, could be required; therefore, an interesting alternative to study the superficial features in produces is the computerized image processing (also known as digital image analysis) that has been widely developed in the food sector. Physical characteristics, such as size, shape, morphology, color and texture properties can be measured by means of image processing (Du and Sun, 2004; Brosnan T and Sun D-W, 2004; Mendoza et al., 2007; Quevedo et al., 2008;).

Digital image analysis allows food quality evaluation by maintaining accuracy and consistency while eliminating the subjectivity of manual inspections. Image analysis have more advantages than other noninvasive techniques such as being cheap, easily adaptable to obtain measurements online, high accuracy, good correlation with visual human inspection, and is very versatile because it allows to obtain a widespread number of features from a simple digital image (Du and Sun 2004).

Careful feature selection of image analysis plays an important role for a successful classification. Some works as (Mery et al., 2010) extract as much as 2,300 features to finally use only a few, 64. This represents a system overload and hinders automatic classification systems from real applications, where very fast classification is needed due to the sheer volume of production.

In this work, we present the feature extraction of three different food produces, namely tortilla, avocado, and mango, described in the following subsections. Then, their relevant features are selected (Section 2) and then they are classified using inductive algorithms (See Section 3). Then we present the results of our experiments (Section 4) and finally we draw conclusions (Section 5).

2 Feature Selection

In this section, we describe the feature selection of three produces: tortilla, mango, and avocado for their latter classification using inductive algorithms. Selecting features carefully is nearly as important—if not more—as the classification algorithm itself. A good feature set must be compact, non-redundant, and one that allows a classifier to correctly separate the classes of interest.

2.1 Color Features

Each image is separated into Red, Green and Blue channels (RGB), and then three interest areas are determined for each image by color-reducing each channel. Those areas bring evidence of the cooking degree on the tortilla surface, or the maturity level on fruits. A tortilla can be considered raw (undercooked), well cooked or burnt (excessively cooked) by counting the surface area occupied by bright spots, average color spots or dark spots respectively. For the case of fruits, the color uniformity suggests little or no damage, while sudden changes of color represent damaged areas.

To reduce the number of intensity levels in an image channel, we establish a threshold. Background pixels are also mapped to a zero-intensity value; so that they appear to be part of the dark spots area but they are filtered out during the color-features extraction process.

Once the three interest areas within each image are selected, the following processes take place: contour identification, surface area filtering and edge characterization; then, features are extracted. We propose the following color features for produce classification

Contour identification. Two morphological *hit-or-miss* operators are proposed. Each structure element is applied four times, rotating 90° each time, and then we use the union of the results. The first structure element, composed by the values $B_{N1} = \{0, \mathbf{\neg 0}, \neg 0\}$ looks for image regions matching one black pixel (the background) followed by two consecutive non-zero values (the produce surface). The second structure element $B_{C1} = \{\neg 128, \mathbf{\neg 128}, 128\}$ looks for regions matching two consecutive non high-intensity pixels followed by a high-intensity pixel, thus, finding raw areas inside the tortilla, or damaged areas inside a fruit.

Color homogeneity (***cHom***) describes a uniform color distribution. For tortillas, this would be the cooking process, and, of course, the average color depends on the corn type the tortilla is made of, the damage area or the mango, or the ripening stage of the mango. In general a uniform specific color represents a better produce (a correctly baked tortilla, a non-damaged mango or avocado). Color will be less homogeneous when there are defects on the produce.

Average Brightness (*Lavg*). This feature identifies, as the name implies, the amount of light from the surface, which ideally should be equivalent throughout the surface, this value varies depending on the type of dough used for making the product in the case of the tortilla, while in the case of fruits, it represents their degree of maturity. This parameter is obtained by an arithmetical mean of all pixels contained in the surface of the produce.

Contrast *(Cnst).* Is the number of local variations in grayscale tones of the image. The more is the variation of the gray tones, the greater is the contrast; a contrast of 0 means that gray levels are constant along the image.

Variance of light intensity (*Lvar*). The non-homogeneous coloration on the surface, is caused by burnt or raw areas and poorly processed corn leftovers (for the tortilla). In the case of the mango and avocado, it represents the amount of a damaged area, or some sickness of the fruit. These defects cause the brightness of the surface not to be homogeneous, which may vary dramatically from one pixel to another. In the ideal case, the variance should be zero, so that for a uniform brightness would expect a value close to zero. For the calculation of this feature, as with the average brightness, all pixels of the surface are used and then the variance of these values is used.

Raw areas (*rawA*). The raw areas represent sections of dough that did not reach the proper cooking and have a lighter color than the rest of the surface. As with the burnt areas, the extraction of the obtained raw areas is obtained from the surface segmentation and calculation is carried out indirectly by counting the pixels of the edges.

Burned areas (*burntA*). Burned areas represent sections of varying sizes of burnt dough produced by an excess of cooking. This feature represents also the damaged areas in fruits. Coloring of these areas is common to any hue of the tortillas or fruits, making it easy to identify. For its identification we use the border extracted as described previously with the *hit-miss* transformation, by filtering the edges of the burned areas from the produce. Obtaining this feature is done in an indirect way, because by counting the edge borders we infer that as there are more edge pixels, the size of the area would be greater.

2.2 Texture Features

The texture parameters described here provide detailed information about the structural changes that occur in the peel during the ripening process of fruits (*i.e.* mango and avocado) while the changes of color described above can be used as auxiliary parameters to evaluate and determine the fruit ripeness.

The **angular second moment** (**ASM**) is a feature that measures the homogeneity of the image (Haralick et al., 1973), **Contrast** is a measure of the local variations present in the image, relating the highest contrast to the largest local variations (Haralick et al., 1973; Mendoza et al., 2007). **The fractal dimension (FD)** or fractal texture is a measure of the degree of roughness of the images; higher values of FD mean more complex or rougher grey level images, while lower values of FD can be associated to simpler or smoother images (Quevedo et al., 2008). Finally, **Entropy** measures the disorder or randomness of the image and it is an indicator of its complexity, thus, the more complex the images the higher the entropy values (Haralick et al., 1973; Mendoza et al., 2007).

2.3 Geometric Features

Since shape is important for the tortilla quality assessment, special geometric features were obtained for this purpose. In order to get a discrete representation for the tortilla's border, we divide it into 64 arc segments. Each arc is projected over the horizontal axis and the length of the projection is measured (Watanabe and Matsumoto, 1991; Cai et al. 2004). A characteristic descriptor for each tortilla side is made up with the lengths of the 64 projected arcs (Hastie et al., 2003).

Geometry-related features aim to capture those attributes related to the shape of the tortilla including curvature; symmetry and continuity. A high quality tortilla must have a nearly perfect circular shape with no holes and no bends or breaks along its border. Since a discrete characteristic chain is used to describe the border of the tortilla, this chain is compared with the corresponding chain of a perfect circle as described in (Gupta and Srinath, 1987). If both chains are identical then the tortilla border has the best quality available. The following features were extracted:

Circularity (circ). Its value is calculated by adding up the differences of each one of the diameters with regard to an average.

Defects (dfct). A defect in a tortilla occurs when a small irregularity appears on the edge, perceptibly altering the circularity of the edge section; this change is often abrupt and has a short distance of no more than one centimeter.

Deformations (dfrm). The deformation in a tortilla is along one segment edge with a non-circular tendency. In this segment the edge direction usually has only one direction (straight).

3 Inductive Classification

Michalski and Chilausky (Michalski and Chilausky, 1980) in the early 1980s, developed an expert system based on learning from examples, called pLANTS / DS. It was able to perform diagnostics of diseases of the soybean plant.

One of the most common techniques used to obtain the rules of inductive learning is known as "divide and conquer" (Domingos, 1996). This technique, which appeared in the early 80's, is named after the method applied to construct a rule induction, dividing the initial set of knowledge rules and selecting the rules that provide better coverage rates. Important works using this technique are Michalski, 1983, Michalski et al. 1986; Clark and Tim, 1989, and Rivest, 1987. Several innovations and/or adaptations of the techniques proposed by them arose for nearly a decade after the publication of these mentioned works.

One of these works to improve learning technique was performed by the same Michalski in the mid-1980s. The STAR method is based on the principle of "divide and conquer" and it further allowed the resolution of everyday problems or applications that have large numbers of possible solutions. Finally, it emerged and positioned itself as the BOUNDSTAR and REDUSTAR methodologies.

3.1 The BOUNDSTAR Algorithm Implementation

The implementation of the BOUNDSTAR algorithm yields as result a series of learning rules that will characterize each class. Since the BOUNDSTAR algorithm strives to find a $G(e|E0,m)$ set, then: e is the event from $E0$ such as ($e \in E0$), m is the set of events that best characterizes a specific class. In our case-study we have m1, m2 and m3 for selecting class1, class2, and class3 respectively.

LEF is the decision criterion that determines the preference order for the events selected by m, considering the class coverage percentage. As the coverage grows, so will the preference. The complete algorithm flows as follows:

Pseudocode for the BOUNDSTAR algorithm

1. By using the LEF criterion, m1 events that best characterized class1 are obtained from the e events. These m1 events are ordered and then are moved to the PS1 set.
2. Each one of the PS events is extended by conjunction with the new events obtained in step (1).
3. Again, the LEF criterion is used to find a new set of events that will be aggregated to a new PS set. Those events that won't be part of the new PS set will be set aside in an "always-available", called ED set.
4. The complex features that strongly characterize the class selected by m1

are found and selected within the PS set and copied into the SOL set.

5. PS1 is again extended by conjoining its elements with those in the ED and PS sets. These sets are evaluated by LEF and only the events with the best covering percentages continue to the next stages.
6. Return to step (4) until the stop criterion is met.

For the purpose of this research, the stop criterion is finding a strong characterizer among the preserved sets, or having an empty ED set. When the algorithm stops because of this last condition, the selected solution is the best qualified by LEF. The above algorithm is repeated for m2 and m3, and that is the way in which the characterization rules are obtained.

The last step in the algorithm is the learning rule performance's analysis. That rule later serves as a classifier over a set of non-ordered samples. During the classification process, new samples are assigned to one of the three classes, or to a set of non-classified samples.

At the end of the classification stage, the learning rule's efficiency is evaluated using the precision and recall concepts.

4 Experimental Results

In this section we will present results for classifying three different produces with the aforementioned feature characterization and inductive analysis.

4.1 Tortillas

We obtained a sample of 600 tortillas, from three kinds of commercial establishments, 200 from each kind. With help from some experts in food engineering, a model of the perfect tortilla made from each possible type of corn was defined and then we proceeded to apply the induction classification. We learned from the first half of 300, and then we evaluated with the remaining 300. Details on the feature extraction of the 300 images of tortilla during the learning phase can be seen in (Moreno-Armendáriz *et al.*, 2013). In **Table 1** the set of solutions that characterize classes better, after applying the REDUSTAR algorithm are shown in bold.

Table 1. Induced rules for classifying tortillas. The rules to be used in the generalization are shown in bold

Class	Solution set	C 1	C 2	C 3
	$burntA < 220 \wedge circ < 60 \wedge Lavg < 50$	38	4	0
1	$\mathbf{rawA > 1200 \wedge Lavg < 50}$	**96**	**0**	**10**
	$0.3262 < dfrm < 0.4452 \wedge Lavg < 50$	52	0	0
2	$\mathbf{Lavg > 50}$	**0**	**100**	**0**
	$Lvar < 85.5 \wedge 0.3262 > dfrm < 0.4452$	0	0	63

3	220 < *burntA* <450 Λ *Lvar* < 91	15	0	72
	***Lavg* < 50 Λ *rawA* < 1200 Λ *circ* > 60**	**0**	**0**	**90**

Table 2. Classified samples. The rows are read the actual class and columns are the class to which they were assigned according to their features and the learned rules of knowledge

		Classification			
		Class 1	Class 2	Class 3	No class
	Class 1	82	0	16	2
Real	Class 2	0	100	0	0
Class	Class 3	2	0	97	1

4.2 Avocado

A computer vision system similar to that described by Pedreschi et al., (2004) was employed to capture the images (1600 x 1200 pixels RGB color and JPEG format). Samples were illuminated using four fluorescent lamps, with a color temperature of 6500 K. Lamps (60 cm long) were arranged in the form of a square, 35 cm above the sample and at an angle of 45° in relation with the sample. Twenty images were obtained for each day of the maturation kinetic (two for each avocado). Each sample was placed in front of the camera in the same position and orientation. Images were obtained using a color digital camera that positioned vertically over the sample. Images of two faces of the avocados were taken on a matte gray background using the following camera settings: manual mode with the lens aperture at f = 2.8 and speed 1/15 s, no zoom and no flash.

The experimental data set was restructured to account for each avocado-side image as a distinct pattern. By doing so, we could set a matrix with 240 rows, one for each pattern (2 images of each avocado during each of the 12 days of the experiment) and 3 columns, one for each digital color parameter (L^*, a^* and b^*). This matrix (*SM*) was used as a supervision sample for the rest of the process.

Following the BOUNDSTAR algorithm, we ranked each feature according to its discrimination capability (Jollife, 2002). In such ranking, the most relevant feature was a^*, followed by b^* in second place and L^* at the end. A weight value in the interval [0,1] is assigned to each feature based on this ranking.

Next we classified the samples using the previously obtained rules, taking as an input a new pattern (the digital image of one side of an avocado) and as an output the maturity stage of the respective avocado.

Statistical analysis. The results were expressed as averages with their standard errors. We applied a one-way analysis of variance (ANOVA) with Tukey's multiple comparison tests for statistical comparisons of data. Ripening classification was developed based on two experiments, and for both cases, 240 images were used (2 images of each avocado during 12 days of the experiment, and 10 avocados per day, for 240 patterns). A first experiment was carried out exclusively with the three digital color parameters (L^*, a^* and b^*) showing that the a^* parameter presented the highest weight value (0.6), followed by b^* and L^* (0.3 and 0.1, respectively). The second experiment, which did not include b^* and L^* parameters, was done employing the six more relevant features (a^* 0.5, Correlation 0.2, ASM 0.2, IDM 0.05, FD 0.025, and Entropy 0.025). The BOUNDSTAR algorithm ranked both sets of features. In the first experiment, a successful classification was found, where 58 of 72 images were properly classified, which represents a percentage of **80.5%.** In the second experiment, 59 images of 72 for the validation phase could be correctly classified, which corresponds to **81.9%.** In both experiments, the chromaticity coordinate a^* was the parameter that described better the ripening process of avocados Hass.

4.3 Mango

After taking mangoes' photographs as described for the avocado in the previous section, we used mathematical morphology for image processing. The morphological operators used were Bot-Hay and Top-Hat used for defect segmentation. We used the feature *burntA* to quantify the damaged areas, as described in Section 0.

Once the mango's damaged surface has been quantified, we classified it according to the Mexican norm NMX-FF-058-SCFI-2006, since it establishes damage tolerances for each mango class. Herrera-Corredor et al. (2007) sets out the different types of damage a mango can show, and also, the expected damage tolerance for each class. That norm establishes 3 mango quality classes: Extra class, First class and Second class. In order to classify mangos, no distinction is made about the various defects, such as illness or mechanical damage that a mango can show. Therefore, the image segmentation processes (*burntA*) just detect any damaged surface unit regardless of the type of defect it represents. Once both mango sides' images are analyzed and the total damaged surface is calculated in square centimeters, the following formula from the Mexican norm, is used to immediately deduce the quality class of each mango sample: Minimum damage: area $\leq 23\text{mm}^2$, High damage: area $> 30\text{mm}^2$ and area $\leq 49\text{mm}^2$, Critical damage: area $> 49\ \text{mm}^2$.

The proposed methodology for the analysis of the Manila Mango quality was tested over a 334 images set corresponding to 167 mangoes. This set was previously classified as follows: 27 mangoes for Class 1, 68 for Class 2, and 72 for Class 3. Classification results are shown in **Table 3**, from which an accuracy of 80% is calculated.

Table 3. Confusion matrix resulting from the classification

	Class 1	**Class 2**	**Class 3**
Class 1	27	0	0
Class 2	20	48	0
Class 3	3	10	59

5 Conclusions

This paper presents three study cases where digital image analysis and inductive characterization techniques have been successfully applied to improve the quality inspection process. Three different basic food products were studied: Avocado, Manila Mango and Tortillas. Each one of these products has some special and particular features that complicate the quality inspection process, but the general technique of inductive characterization with a reduced set of features presented in this work, has great accuracy and significantly lower costs.

An example of the general process of characterization can be seen in **Table 1**, where early complex features achieve the percentages of coverage. From this learning stage it can be appreciated, as anticipated in the extraction of features, that not all features that are useful for the characterization, however, there are complex features capable of characterizing a class above the other with excellent results. Examples are traits for the tortilla *Lavg* > 50 and *Lvar* > 91, which are close to 100% coverage in the class of interest, class 2. After the implementation of the BOUNDSTAR algorithm, we obtained the rule set shown in bold in in **Table 1**. This rule set represents the best solutions for each class and it can be used independently for different purposes.

We have found that the inductive characterization of three classes of producers is achieved with high percentages of coverage and precision; particularly in the case of Group 2 of tortillas presents a coverage of 100%. Importantly, despite the diversity of variables involved it was possible to find distinctive patterns of each. The proposed color and geometric features were useful for achieving this classification. The most important features in the classification, given the high percentage of coverage for the desired classes were color features. Significantly, color features become extremely important in characterizing when considering the preference of the consumer.

In general, we can say that image features obtained by image processing provide a good description of the quality of produces. In addition, the color and texture features evaluated from the images, in particular FD values, showed an adequate correlation with the traditional quality parameters. However, in this particular study, the image color features resulted in better information than the image texture parameters when a reduced number of samples and images features were used. Particularly, when applying only three image color features an adequate classification of the avocados Hass was obtained. Nevertheless, the chromaticity coordinate a^* was the best parameter to describe the ripening process. These results confirm that computer vision systems, based on image processing, can be used to determine the quality of produces. The existence and commercial availability of these systems greatly impacts on the logistic operation and budget of independent farmers and small food industries. Moreover, critical systems which analyze and determine the quality of agricultural products, such as fruits or vegetables, or even other products such as tortilla, could be very well designed and implemented following the presented methodology.

As a future work, we plan to test our implementation on hardware to make it fully automatized.

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