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Full Length Research Paper

Tomato quality evaluation with image processing: A review

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Tomatoes are in high demand because the world population consumes them daily. This research aims to improve tomato production and fruit quality through fruit measurement methods, which have a low impact factor on the fruit and plant during measurements. In the present paper, we present a review of the main attributes, such as color, ripening rate, firmness, shape, size and composition, that determine tomato fruit quality for final consumers; we also overview the methods (invasive destructive and invasive nondestructive) currently used to evaluate these attributes. The future trend in attribute analysis involves the development of portable, low-cost devices that take images directly from crops in the field to instantly determine quality characteristics.

Key words: Tomato quality, nondestructive method, image processing.

INTRODUCTION

According to data coming from the Mexican Ministry of Agriculture, horticulture constitutes 18% of Mexico's agricultural production and half of its agricultural exports. Due to the highly labor-intensive nature of horticulture and horticultural processing, these fields generate more than 20% of the total labor-days within the Mexican agricultural sector. Moreover, the horticultural sector has flourished under globalization, diversifying exports to the US market and increasing the scale of production. The tomato agro-industry is by far the most important in Mexico in terms of exports and employment (Barron and Rello, 2000). Tomatoes, commonly consumed in daily diets, are a major source of antioxidants (Sgherri et al., 2008). They are a seasonal crop, and their availability is limited during certain seasons (Rodriguez-Lafuente et al., 2010). Tomatoes find numerous uses in both fresh and processed forms. Processed products include ketchup, sauces, pastes and juice. A substantial amount of research has been conducted to determine the ability of tomato derivatives to prevent certain types of cancers and cardiovascular diseases. These studies have demonstrated that the thermal treatment of tomatoes (in every commercial product) is positively correlated with a lowered risk of cancers of the digestive tract and prostate. Today, the market is showing an increased interest in products from environments with intermediate humidity. These products combine increased stability from lower water activity with good nutritional and organoleptic characteristics (Muratore et al., 2008). Soil warming has been shown to increase plant growth, improve crop productivity and reduce energy consumption (Gosselin and Trudel, 1984). Firmness and color, used to determine fruit maturity, are important attributes of tomato quality for both the fresh and processed markets. Fruits that are soft when ripe (not well ripe) are considered to be of poor quality by the consumer and processor. An homogeneous red color is considered desirable by both groups, but it is much more important to the processor than to the consumer. The concentrations of organic and ascorbic acids increase with the maturity of fruits; maximum concentrations were reported during the pink stage of ripening, and concentrations declined slightly during the red stage. The amount of sugars increased with maturity, with fructose being the predominant sugar. The influence of CO_2 enrichment on fruit growth, firmness and color, its effect on the concentrations of ascorbic acid, organic acids and

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sugars and the activities of sucrose synthase and sucrose phosphate synthase were determined at various stages of maturity in tomato fruits. CO_2 enrichment is commonly practiced in greenhouse crops because it increases yields and, consequently, profit. CO_2 enrichment increases the net photosynthesis, dry weight, plant height and number of leaves and lateral branches; it also enhances the fruit growth and coloring during the development of potted plants, cut flowers, vegetables and forest plants (Islam et al., 1996). All of these factors have influenced the development of noninvasive methods and technologies used to determine quality attributes in tomato production.

OVERVIEW OF TOMATO PRODUCTION

Worldwide, tomato plants are grown in several environments. There are specific zones in which it is impossible to grow the crop in open fields because of extreme climate conditions (Netherlands, northern Europe), and there are zones in which it is possible, but only in specific seasons (México). Currently, the trend is toward protected production in controlled greenhouse environments because this technique is highly efficient and has the potential to increase food production to meet market demands (Rico-García et al., 2009). According to the Food and Agriculture Organization of the United Nations (FAO), advantages of greenhouses include the following: protection against extreme climatic conditions; controlled heating, cooling, shading and CO_2 enrichment; out-of-season harvests; improvements in crop quality; ground structure preservation; ability to sow selected materials; considerable production increases; reduced production costs; more efficient use of the growing area and lowered use of pesticides. Similarly, new, automated technologies are being promoted to help the grower in greenhouse operations (Soto-Zarazúa et al., 2010).

Tomato quality

There are four types of tomatoes: milano, chonto, cherry and industrial (Jaramillo et al., 2007). The milano type tomato is generally used in salads and consumed in the green mature or red state (restaurants prefer the green mature state). This type has significant commercial value and palatability. The chonto type is consumed when fresh and is used in the preparation of stews or pasta. The cherry type has very small fruits, grouped in clusters of 15 or more and consists of many different colors including yellow, red and orange. The cherry type is consumed fresh as a snack, in cocktails and as a garnish. The industrial type is characterized by large amounts of soluble solids that make it attractive for processing, primarily in the production of sauces and pastas.

The tomato fruit is a berry, and different attributes, such as color, ripening rate, firmness, size, shape and composition, determine its quality. Mature fruits can be red, pink or yellow. Direct exposure to the sun increases the intensity of greenness on the fruit's shoulders and, in some cases, produces a yellow coloration; capping the fruit helps to reduce this phenomenon (Jaramillo et al., 2007).

Tomatoes contain a large quantity of water **(**93.5**%)**, calcium (0.07%) and niacin, all of which are of great importance in the metabolic activities of humans. Tomato, a good source of vitamins A, C and E, helps to protect against diseases (Olaniyi et al., 2010; Jaramillo et al., 2007). Consumers consider a tomato to be of high quality if it has good color and uniform ripening as well as acceptable firmness, shape, size, composition and taste; producers consider these qualities in addition to a high nutritional content and a long shelf life.

Color

Color in tomato is the most important visible characteristic used to assess ripeness and postharvest life, and it is a major factor in the consumer's purchase decision. The degree of ripeness is usually estimated visually by human graders who compare the tomato color to a classification chart. This manual practice of tomato maturity classification often results in errors due to human subjectivity, visual stress and fatigue (De Grano and Pabico, 2007). Human identification of color is complex because sensations such as brightness, intensity, lightness and vividness modify the perception of primary colors (red, blue and yellow) and their combinations (e.g., orange, green and purple). Colors can be located within the color sphere defined by three perpendicular axes: L* (from white to black), a* (from green to red) and b* (from blue to yellow) (López and Gómez, 2004).

As color is an indication of tomato ripeness, a green to red gradient can also be used to assess the stage at which a tomato should be harvested and consumed. According to Jaramillo et al., 2007, tomato ripeness can be classified into six stages:

Stage 1 - Green mature: The entire surface of the fruit is green, with the tone of green varying according to variety.
Stage 2 - Breaking: A color other than green appears on not more than 10% of the fruit surface.
Stage 3 - Turning: Between 10 to 30% of the fruit surface is colored pale yellow, pink, red or a combination of these.
Stage 4 - Pink: Between 30 to 60% of the surface shows a pink or red color.
Stage 5 - Light red: Between 60 to 90% of the surface is red.
Stage 6 - Red: More than 90% of the surface is red.

Ripening

The tomato fruit is a climacteric fruit, and therefore, it continues maturing after it has been harvested. This characteristic must be considered at the time of harvesting. The physiological maturity is clear because the apical part of the fruit begins to show an orange coloration while the rest of the fruit remains green. The most visible sign of organoleptic ripening in a tomato is the change from green to red due to the decomposition of chlorophyll and the synthesis of lycopene and carotenoids. The second characteristic sign of tomatoes' maturity is the softening that accompanies the change of color. This change is caused by the synthesis of the polygalacturonase enzyme, which acts to degrade the cell wall. The production of this enzyme is initiated by ethylene, which helps to explain the importance of ethylene in the natural and artificial ripening of tomato (Jaramillo et al., 2007).

Firmness

Other than visual appearance, the most important factor in tomato quality is firmness. Tomato quality is influenced by the hardness of the epidermis, the firmness and the internal structure of the fruit, which vary widely among cultivars. The production of the cell wall-solubilizing enzyme (polygalacturonase) during maturation plays a significant role in texture changes (Jaramillo et al., 2007). Generally, firmness refers to the force required to pierce the tomato with a standard probe. The most common technique for obtaining this is the Magness-Taylor (MT) firmness measurement, a destructive type of test method. Most of the non-destructive test (NDT) methods (e.g., acoustic firmness, laser air-puff and near IR) require expensive and cumbersome instrumentation (Ranatunga et al., 2009).

Shape

According to Jaramillo et al. (2007), there are several forms of tomato fruit in the market (Figure 1). Tomatoes are differentiated according to their intention for either fresh consumption or industrial processing or according to their external shape. A tomato's form depends on the type, the growing treatment (fertilization) and the chemical modification of seeds to get a specific form or composition.

Size

According to the four basic types of tomatoes and hybrids, the major attributes (Table 1) that determine size are weight, form and diameter.

Composition

Tomatoes are rich in vitamins A, B1, B2, B6, C and E and in minerals such as potassium, magnesium, manganese, zinc, copper, sodium, iron and calcium. Tomatoes have a high nutritional value because they include proteins, carbohydrates, fiber, folic acid, tartaric acid, succinic acid and salicylic acid (Jaramillo et al., 2007). A summary of the important nutrients is shown in Table 2. Table 3 shows the proposed appropriate values for tomato plants during their development.

Tomatoes are rich in lycopene, the pigment that gives them their characteristic red color. Lycopene is the most potent antioxidant, but tomatoes also contain the antioxidant glutathione, which helps to cleanse the body of toxic products and prevents the accumulation of heavy metals (Jaramillo et al., 2007).

METHODS TO ESTIMATE TOMATO QUALITIES

Currently, optimal harvest dates and predictions of storage life are mainly based on practical experience, but leaving these critical decisions to subjective interpretation implies that large quantities of fruit are harvested too soon or too late and eventually reach consumer markets in poor condition (Gómez et al., 2006). The main disadvantage of the majority of these techniques is that they are not practical for cultivars or storage stages. Moreover, most of the techniques require the destruction of the samples used for analysis. To illustrate the differences between the methods, they are separated into three categories: invasive-destructive, invasive-nondestructive and noninvasive.

Invasive-destructive

These methods are applied to separate parts of the plant; the fruit and occasionally the entire plant may be subjected to further analysis, often in the laboratory. These methods, which require calibration prior to each test, are sensitive to white noise and have large maintenance costs. They are generally laborious and time consuming because, in most cases, the fruit or plant must be completely destroyed and ground prior to analysis.

Rico-García et al. (2009) used a destructive method to measure the area of leaves. In this method, all leaves were removed, and the leaves area was determined in the laboratory by image analysis.

Invasive-nondestructive

Invasive-nondestructive methods are those that require contact with the plant or fruit to obtain the necessary measurements, but do not require cutting or destroying parts of the plant or fruit.

Geostatistical modeling describes the phenological development and the increase in dry matter of the different tomato plant organs from the planting date to the end of harvest under dynamically varying solar radiation intensities, greenhouse temperatures and CO_2 concentrations (Bojacá et al., 2009). The objectives here are (1) to study the relationship between outside global radiation intensity and greenhouse air temperature distribution, (2) todetermine the reliability of geostatistical methods in estimating the horizontal temperature distribution and (3) to establish the relevance in terms of plant development and yield of the estimated

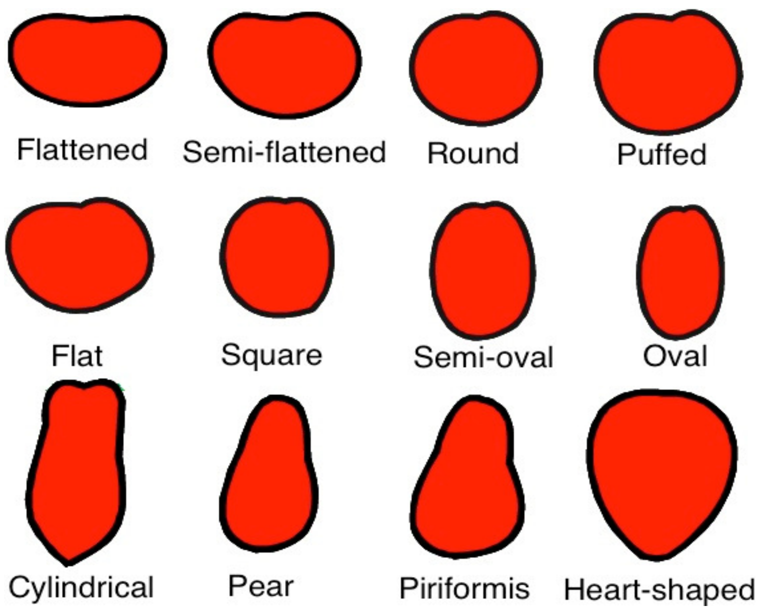

Figure 1. Forms of the tomato fruit. Source: Adapted from Jaramillo et al., (2007).

Table 1. Weight, form and diameter of tomato fruits of different types (Jaramillo et al., 2007).

Type	Weight (g)	Diameter (cm)	Shape
Milano	200 - 400		1 or 2
Granitio	195	-	1 or 2
Astona F1	214	-	1 or 2
Aurora F1	220 - 270	7.6	2 or 4
Rebeca F1	180	5.2	3
Sheila F1	165	5.6	3
Reina F1	200 - 250	8.7	1 or 4
Rocío	280 - 300	-	1 or 4
Monalisa	190	6.4	1 or 2
Titán F1	178	-	1 or 2
Chonto	70 - 220		3 or 8
Torrano	152	-	3 or 8
9206	152	-	3 or 8
9207	152	-	3 or 8
Débora max F1	140 - 160	-	3 or 8
Débora plus F1	130 -140	4.3	3 or 8
Calima	160	-	3 or 8
Santa fe	160	-	3 or 8
Santa clara	160	-	3 or 8
Kyndio Colombia	157	-	3 or 8
Cherry	10	1 - 3	3 or 10
Industrial	Variable	Variable	3 - 11

Weights and diameters are approximate agree to FAO. 1: Flattened, 2: semi-flattened, 3: round, 4: puffed, 5: flat, 6: square, 7: semi-oval, 8: oval, 9: cylindrical, 10: pear, 11: piriformis, 12: heart-shaped.

temperature distribution inside a greenhouse. Solar radiation is one of the major driving forces that determines the climate of a greenhouse.

A back-propagation neural network was used to predict tomato maturity using reflectance ratios as inputs. Higher success rates were achieved for tomato maturity stage recognition with neural

Table 2. Nutritional composition per 100 g of fresh tomato (Jaramillo et al., 2007).

Element	Quantity
Water%	93.5
Protein (g)	0.9
Fat (g)	0.1
Calories	23
Carbohydrates (g)	3.3
Fiber (g)	0.8
Phosphorus (mg)	19
Calcium (mg)	7
Iron (mg)	0.7
Vitamin A(UI)	1.100
Vitamin B1(mg)	0.05
Vitamin B2(mg)	0.02
Vitamin C(mg)	20
Niacin(mg)	0.6

Table 3. Appropriate content of nutrients in a foliar analysis of tomato (Jaramillo et al., 2007).

		(%)		
N	**P**	**K**	**Ca**	**Mg**
3 - 5	0.4	6	1.25	0.5
		(ppm)		
B	**Mn**	**Fe**	**Cu**	**Zn**
40 - 60	30 - 50	70 - 150	5 - 10	20 - 40

networks than with discriminant analysis (Hahn et al., 1999).

A color image analysis procedure was developed to classify fresh tomatoes into six maturity stages according to the USDA standard classification: Green, Breakers, Turning, Pink, Light Red and Red. Red, green and blue (RGB) images of each tomato were captured and converted to hue, saturation and intensity (HSI) values. Classification was based on the aggregated percentage of surface area below certain hue angles. A tomato maturity index was developed to indicate the degree of maturity within each stage and to provide a continuous index over the complete maturity range (Choi et al., 1995).

The Minolta SPAD-502 was designed to estimate the chlorophyll and nitrogen content of *Eucalyptus nitens* and *E. globulus* foliage. This meter measures leaf absorbance at wavelengths between 650 and 940 nm (Pinkard et al., 2006).

The Minolta Colorimeter (Model CR-200, Minolta Corp., Ramsay, NJ) measures color in terms of the color space L*, a* and b*. The L* value indicates lightness; the +a* value is the red direction; the -a* value is the green direction; the +b* value is the yellow direction; and the –b* value is the blue direction. Chroma, C* = (a*+b*)1/2, indicates the intensity or color saturation, and the hue angle is calculated as hº = arc tangent b*/a*, where 0º = red-purple, 90º = yellow, 180º = bluish-green and 270º = blue (Luengwilai and Beckles, 2010).

A non-destructive method for assessing the maturity of tomatoes was developed using the mechanical properties of the fruit in the falling impact test. The levels of maturity were classified with cluster and discriminant analyses on the primitive impact measurements and their derivatives (Lien et al., 2009).

Noninvasive

The noninvasive methods are those in which direct contact with the plant or fruit is not required to obtain measurements.

The overall goal of precision agriculture is to make cultural operations more efficient, to reduce environmental impact and to enhance crop quality and yields (Mercado-Luna et al., 2010). Noninvasive methods facilitate studies of the characteristics of fruits and plants without affecting their natural growth. Considerable research has focused on the development of non-destructive-invasive techniques for measuring the quality attributes of fruit (Gómez et al., 2006).

Recently, electronic nose technology has introduced the possibility of using aromatic information to assess the ripeness stage. This technology draws on knowledge from a variety of fields, including food analysis. The electronic nose offers a fast and nondestructive alternative to sense aroma and may be advantageously used to predict the optimal harvest date. Commercially available electronic noses use an array of sensors combined with pattern recognition software (Gómez et al., 2006).

IMAGE PROCESSING APPLIED TO AGRICULTURE

Currently, there are several examples of noninvasive systems that have been developed for specific applications in agriculture. Al-Mallahi et al. (2010) developed an algorithm, useful for sorting and grading purposes, that helps to detect in-line potatoes tubers without singulation when they are mixed with clods. The algorithm scans images that include clusters of tubers and clods until it encounters a cluster. A personal computer (PC) is used for processing. Liming and Yanchao (2010) developed an automated strawberry grading system based on three characteristics: shape, size and color. This method is based on image processing, and a PC is used for processing. Mercado-Luna et al. (2010) developed a system that uses color image analysis in RGB to determine the nitrogen concentration in tomato plants. Images of tomato leaves are analyzed on a PC with the image processing toolbox in Matlab Software. Min et al. (2008) designed a system to predict nitrogen concentration in orange leaves using a spectophotometer. Pearson (2009) developed a hardware-based image processing system for high-speed inspection of grains. Chaoui and Sørensen (2008) give a review of the advances and technological needs in ecological agriculture. These include systems for improved soil nutrient management, the control of weeds and pests, the construction of weeding robots and automated transplanting machines and machines that evaluate fruit quality attributes.

Digital image processing

Digital image processing is a methodology that emerged in the 1970s to process simple images without specific applications. Over time, this technique was refined and multiple applications of digital image processing emerged. Image processing and computer vision, an important research area due to rapid technological development, have applications including machine vision, medical imaging, satellite imagery, video, digital cinema and art. The main objective of image processing is to improve the appearance of images and to augment certain details that will be used for further interpretation. The major techniques used in digital image processing that can be applied to determine tomato qualities are thus explained.

Pattern recognition

Pattern recognition is a type of image manipulation in which the input is an image and the output is a description of the image. Image enhancement, automatic visual inspection and image coding are other forms of image manipulation. Pattern recognition has a wide range of applications in fields, such as remote sensing (Chen and Ho, 2008), robotics (Sanz et al., 2005), industry, medicine (Patrick et al., 2010), military uses, computer vision, character recognition, speech recognition and astronomy (Liu et al., 2006). The detection of plant and fruit defects or abnormalities could be the most important application in horticulture. Pattern classification and object counting have interesting applications in areas other than quality control (Hamed, 1997). Pattern recognition has undergone many important developments in recent years, and a number of new applications have emerged (Liu et al., 2006).

Gray-scale images

There are many methods that can be used to modify the characteristics of a captured image. First, acquired RGB-color images can be converted into gray-scale images (Yang et al., 2009). Then, to filter the background, multi-threshold methods can be performed, that is, the R-value in RGB and the S-value in HIS are taken into account (Xiao-bo et al., 2010). These methods, similar to those used by Rashidi and Gholami (2008) to evaluate the volume in kiwifruit, help to determine the shape and size of tomato fruit.

Excess green

The excess green (MExG) method is used to distinguish between plants and soil areas in the identification of weed species. MExG is defined by the mathematical expression: $MExG = 2 \times G - R - B$. With this technique, images must be converted to the corresponding MExG levels by removing red and blue. MExG conversion of red, green and blue (RGB) data involves segmentation to separate weed regions from the background and internal voids (Ishak et al., 2009).

Image segmentation

Image segmentation divides an image into nearly homogeneous regions that are not homogeneous when joined. It is a key step in image analysis, pattern recognition and low-level vision, which is significant for object recognition and tracking, image retrieval, face detection and other computer vision applications. Color images carry much more information than gray-level ones. In many pattern-recognition and computer-vision applications, color information can be used to enhance image analysis and improve segmentation results compared to gray-scale-based approaches. As a result, a substantial effort has been made in recent years to investigate color image segmentation (Tao et al., 2007).

The goal of image segmentation is to extract meaningful objects from an input image. Image segmentation is one of the most difficult low-level image analysis tasks. The inability to adapt the image segmentation process to real-world changes is one of the fundamental weaknesses of model-based object recognition systems.

To recognize different objects or instances of the same object in an image, different sets of local parameters are needed due to changes in local image properties such as brightness and contrast. Changing environmental conditions also affects an image's appearance, requiring the ability to adapt the algorithm parameters for multi-scenario object recognition (Bhanu and Peng, 2000).

The majority of segmentation algorithms produce two-level, or “object and background”, segmentation.

Although this type of segmentation is appropriate for certain classical applications, such as the automatic image analysis of documents or industrial parts, it is not satisfactory for applications with more complex scenes in which several objects must be detected (Boskovitz and Guterman, 2002). The Gauss Mixture Model (Pyun et al., 2007), Binary Partition Tree (Lu et al., 2007) and Radio Cut (Wang and Siskind, 2003) are methods applied during segmentation in image and video processing.

CONCLUSIONS

Recent developments in agricultural technology have led to the demand for a new era of automated, noninvasive methods that leave the crop intact and do not interfere with its natural growth.

Image processing is very useful for the area of agriculture, allowing us to develop systems that do not interfere with the plant. At the same time, we can measure fast and very close to testing done by laboratories.

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