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REVIEW ARTICLE

Image Processing Tools and Techniques Used in Computer Vision for Quality Assessment of Food Products: A Review

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Abstract

With high expectations for food products of high quality and safety standards, image processing techniques used in computer vision have been applied increasingly for food quality evaluations. This paper reviews developments of image processing tools and techniques for food quality evaluations, which include principles of image processing; imaging systems; and low-, mid- and high-level image processing. Low-level image processing involves noise removal and contrast enhancing, mid-level image processing requires segmentation based on thresholding, gradient, region, and classification methods are also included. This paper presents the significant elements and important aspects of image processing techniques used in computer vision systems and emphasizes the considerable research of image processing techniques for the inspection and grading of food products.

Keywords: Image, Imaging, Image processing, Techniques, Computer vision.

1. Introduction

Food quality is the characteristic of a food that makes it acceptable to consumers and it is a key factor for the modern food industry to focus on because a high-quality product is the basis for success in today's highly competitive market. Quality includes external factors such as texture, flavor, appearance (size, shape, color, gloss, and consistency) (Azman *et al.*, 2007); grade standards, and various internal (chemical, physical, and microbial) factors. Thus, to satisfy the increased awareness, sophistication, and greater expectation of consumers, it is very necessary to improve quality evaluation techniques of food products (Brosnan and Sun, 2004). Quality evaluation in the food industries still heavily depends on manual inspection, which is tedious, laborious, and costly, and is easily influenced by physiological factor, inducing subjective and inconsistent evaluation results (Du and Sun, 2006a; 2006b). So, to achieve valuable quality control for food products, it should not be dependent on human errors during inspection, and therefore, quality control systems must be automated. When quality evaluation is achieved automatically, then production speed and efficiency can also be improved. In addition, evaluation accuracy can be increased, accompanied by reduction in production cost (Sun and Brosnan, 2003). Consequently, computer vision systems have been increasingly used in several food operations, such as sugar, wheat, and vegetable industries (Marquez and Anon, 1986; McDonald and Chen, 1990) for quality evaluation purposes so far as a rapid, economic, consistent, and even more accurate and objective inspection tools (Sun, 2000; 2008). Although both outer and inner quality information can be collected by an automatic grading system in a factory, computer vision is more effective for measuring outer parameters (Lee *et al.*, 1999; Majumdar and Jayas, 2000a; 2011b; Shahin and Symons, 2001; Paliwal *et al.*, 2003; Shigeta *et al.*, 2004; Shahin *et al.*, 2004; Qiao *et al.*, 2004; Lorestani *et al.*, 2006; Singh *et al.*, 2013).

Image processing techniques are being used increasingly in the field of agricultural and food products for quality assurance purposes. For instance, an automated quality verification system (Njoroge *et al.*, 2002) and a multiproduct grading system (Kondo *et al.*, 2005) have been proposed for agricultural products. In addition, to estimate size, sort color, classify shape, detect bruises or scar tissue, and to predict the mass of fruits, a number of algorithms have been developed and applied so far during image processing. Image processing modifies pictures to improve them (enhancement, restoration), extract information (analysis, recognition), and change their structure (composition, image editing). Images can be processed by optical, photographic, and electronic means, but image processing using digital computers is the most common method because digital methods are fast, flexible, and precise (Anonymous, 1996). The use of image processing is now gaining interest for the evaluation of internal (sweetness, acidity, inner diseases), external (size, color intensity, color homogeneity, bruises, shape, stem identification, surface texture, mass), and freshness quality of produce. The application potential of image processing techniques, to evaluate food quality in food industries has long been recognized.

Being an objective, consistent, quantitative, rapid, noncontact, and nondestructive evaluation tool, computer vision has been attracting much research and development attention from the food industry and rapid development has been increasingly taking place on quality inspection for a wide range of food products (Timmermans, 1998; Sun, 2004). The food industries ranked among the top 10 industries using computer vision technology (Gunasekaran, 1996). Medical computer vision or medical image processing is probably the most prominent application. It is characterized by the extraction of information from image data for the purpose of making a medical diagnosis for a patient. Generally, image data are in the form of microscopy images, X-ray images, angiography images, ultrasonic images, and tomography images (Anonymous, 2009).

Various image processing techniques have been developed during the last decade for food quality evaluations and have found many applications in diverse fields of scientific, commercial, and technical endeavors. A considerable effort must therefore to be made to review and describe the tools and techniques that are used in computer vision to facilitate image processing. So, the aim of this paper is to review and investigate recent applications of image processing tools and techniques that are adoptable or have already been adopted by the food industry. The feasibility of various techniques used in computer vision for food quality evaluation is also discussed. This review can serve as a foundation for applying the processing techniques available and also for the development of new processing techniques in computer vision systems.

2. Image Processing

In computer vision, grouping parts of a generalized image into units that are homogeneous with respect to one or more characteristics (or features) result in a segmented image. A segmented image extends the generalized image in a crucial respect: it contains the beginnings of domain- dependent interpretation. So, imaging is the representation or reproduction of an object's outward form especially a visual representation or formation of an image**.** And an image is a representation, likeness, or imitation of an object or thing, a vivid or graphic description, something introduced to represent something else. Usually, it is a condensation or summary of the information of the object it represents. Ordinarily, an image contains less information than the original object and is always incomplete, yet in some sense it is an adequate representation of the object.

Owing to imperfections of image acquisition systems, the images acquired are subject to various defects that will affect subsequent processing (Zheng and Sun, 2008b). The field of digital image processing for such corrections refers to image processing by means of a digital computer. A fundamental computer vision system generally includes the following functions: lighting (dedicated illumination), optics (to couple the image to a sensor), sensor (to convert optical image to an analog electronic signal), analog-to-digital (A/D) converter (to sample and to quantize the analog signal), image processor/vision engine (which includes software or hardware to reduce noise and to enhance, process, and analyze an image), computer (decision-maker and controller), operator interface (terminal, light pen, touch panel display, and so on, used by operator to interface with the system), input-output (communication channels to the system and to process it), and display (television or computer monitor to make visual observations) (Zuech, 2000). Among these functions, processing is the act of subjecting something to a process, a series of actions or operations leading to a desired result by altering its form in a desired manner that takes an image and makes it into an image, starting with one image and producing a modified version of that image. Digital image analysis is taken to mean a process that takes a digital image into something other than a digital image, such as a set of measurements of the object (contained by the image). Before processing, an image must be converted to its numerical form, which is called digitization. A digital image is composed of a finite number of elements, each of which having a particular location and value, referred to as picture elements, image elements, pels, and pixels. The term pixel is most widely used and denotes the elements of a digital image (Gonzalez and Woods, 2002). The term digital image processing, however, is loosely used to cover both processing and analysis. Table 1 displays some important commonly used image processing terms.

3. Image Processing Techniques

Table 1: Commonly used image processing terms

Terms	Definition
Algorithm	An algorithm is any program the user uploads that can be used to process the images, extract features, or classify an image.
Binary image	Image where pixels have only two values, generally 0 and 1.
Brightness	The gray level value of a pixel within an image that corresponds to energy intensity. The larger the gray level value, the greater the brightness.
Closing	A dilation followed by an erosion. A closing fills small holes in objects and smoothes the boundaries of objects.
Contrast	The amount of gray level variation within an image.
Dilation	A morphological operation that enlarges the geometrical size of objects within an image.
Erosion	A morphological operation that reduces the geometrical size of objects within an image.
Gama correction	Gamma correction allows users to better match the intensity of their prints to what they see on their computer screen (CRT).
Gray scale	Range of gray shades, or gray levels corresponding to pixel values that a monochrome image incorporates.
Histogram	A graph showing the number of pixels in an image at each different intensity value found in that image.
Image	A two-dimensional function, f(x, y), where x and y are spatial (plane) coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point.
Image Analysis	Image analysis is the extraction of meaningful information from images; mainly from digital images by means of digital image processing techniques.
Image processing	Encompasses various processes and analysis functions that we can apply to an image.
Image preprocessing	The pre-processing task involves some procedures to prepare the images to be ready for image processing.
Imaging	Any process of acquiring and displaying images and analyzing image data.
Kernel	A kernel is a (usually) smallish matrix of numbers that is used in image convolutions.
Mask	Refers to a small image used to specify the area of operation to take place on a larger image in an algorithm.
Matrix	Image representation using MxN matrix is a 90° clockwise rotation of the conventional two-dimensional Cartesian coordinate representation.
Morphology	Originally comes from the study of forms, of plants or animals. Image morphology represents study of topology or structure of objects from their images. Morphological processing refers to certain operations where an object is "hit" with a structuring element and thereby reduced to a more revealing shape.
Noise	Degradation of image due to equipment (such as sensor, camera misfocus), type of modality, motion, turbulence, and so on.
Opening	An erosion followed by a dilation. An opening removes small objects and smoothes boundaries of objects in the image.
Pixel	Slang for picture element, the smallest element if an image.
Preprocessing	Noise reduction, image enhancement, and so on.
Segmentation	Partitioning an image into objects of interest
Thresholding	A value used to segment the gray level values of an image into two different regions. Also called the binarization of an image.

Image processing techniques generally consists of the following 5 steps, also shown in Fig 1a, which are (1) image acquisition operations to convert images into digital form; (2) preprocessing operations to obtain and improve an image with the same dimensions as the original image; (3) image segmentation operations to partition a digital image into disjoint and nonoverlapping regions; (4) object measurement operations to measure the characteristics of objects, such as size, shape, color, and texture; and (5) classification operations to identify objects by classifying them into different groups (Du and Sun, 2004). Fig 1b, however, shows different steps of image processing techniques in terms of low-, mid- and high-level.

3.1 Low Level Image Techniques

Low-level processing includes image acquisition and preprocessing.

3.1.1 Image Acquisition

Image acquisition, the first step in any image processing system, is the capture of an image in digital form. It is the transfer of the electronic signal from the sensing device to numeric form. Its precision generally depends upon factors such as specification of illumination system, quantum efficiency and spectral range of camera/sensor, illumination techniques, and field of application (Martin, 2007). Among these, illumination is an important prerequisite in image acquisition for food quality evaluation, since the performance of the illumination system can greatly influence the image quality and play an important role in the overall efficiency and accuracy of the system (Novini, 1995). A wide variety of light sources and lighting arrangements are, however, available (Tao *et al.*, 1995), a well-designed illumination system can help to improve the success of the image processing and analysis by enhancing image contrast (Novini, 1990; Sun, 2000).

During the last decades, considerable research effort has been directed at developing techniques for image acquisition. A very intensive field of research in image acquisition is the development of sensors. Widely various configurations of sensors have been used to convert images into digital form. The sensors such as charge-coupled device (CCD) and CMOS (complementary metal oxide silicon**)** camera are widely used to obtain images of food products. The CCD camera is frequently employed by image processing systems for food quality evaluations. It has been widely used for quality classification, physical characteristic detection, and property estimation of food products. On the other hand, CMOS image sensors have intrinsic advantages (low power consumption, low cost, high speed imaging, integration capability, radiation hardness, etc.) that make them well suited not only for low-cost imaging markets but also for high performances applications such as high end Digital Still Photography, High-Definition Television and several space applications. These sensors are two main kinds of solid state image sensors which are widely applied at present. CCD and CMOS image sensors used for photons detection are organized as arrays of photo detectors that deliver an electrical signal related to the amount of photons that fall on the pixel surface during the integration time. They both use the photoelectric effect in silicon, in either a photo gate or a photodiode detector (Magnan, 2003; Zhang *et al.*, 2008). Since, it is difficult to evaluate food quality in the ordinary spectral region with a single camera, the CCD and CMOS image sensors will remain complementary and long term competition, and flourish the image sensor market together (Zhang *et al.*, 2008) in predictable future. For example, Park *et al.* (1998) implemented a multi-spectral imaging technique with 4 CCD cameras in an on-line inspection system to separate wholesome and unwholesome chicken carcasses. Li *et al.* (2002) developed a novel automated experimental system for sorting apple surface defects based on computer image technology. In their study they mounted above and below the conveyor 2 CCD cameras, with interference band-pass optical filters (840 nm). Omid *et al.* (2010) developed a machine vision system consisted of two CCD cameras for computing the volume and mass of citrus fruits. So, to achieve a basically complete inspection of food products, it is necessary to use more than one camera to obtain food images free of geometric distortion from different directions.

In spite of this, images are often degraded because of distortion and noise in the camera and the optical system. So, to preserve image quality reasonably enough for valuable information retrieval before the beginning of analysis and processing, digital images must be preprocessed. By preprocessing the image is enhanced. Image preprocessing refers to the initial processing of the raw image data using operations such as noise reduction, contrast enhancement, smoothing, image sharpening, transformation (converting the original 3D image to 2D pixel values), correction for blurring and focusing, correction of geometric distortions, and gray level correction, etc. (Shirai, 1987; Sonka *et al.*, 1999; Sun, 2000; Panigrahi *et al.*, 2001**;** Gonzales *et al***.,** 2004). Faucitano *et al.* (2005) used the free hand mask cutting tool of Corel Photo-Paint 8.2 (Coral Cooperation, Canada), an image editing program, to cut out the muscle image with no background in their study of pork marbling characteristics.

3.1.2 Preprocessing

3.1.2.1 Noise Removal

An image can have different types of noise due to the various means of image capturing systems, such as read-out noise, wiring noise, electronic noise, and extraneous noise like as periodic stripes introduced during the digitization process. All these noises must be removed for good image quality; and by suppressing undesired distortions, or by enhancing important features of interest before digitizing and storing the images in computers that can be possible. Averaging and Gaussian filters are often used for noise reduction with their operation causing a smoothing in the image but having the effect of blurring the edges. In spite of -

Fig 1a: Configuration of common image processing system (Du and Sun, 2004)

this, the most efficient and feasible approach for image noise removal is averaging the image by itself (Zheng and Sun, 2008a). Yam and Papadakis (2004) averaged values for multiple pixels to reduce the noise in the plots during the measuring and analyzing the color of food surfaces. The simplest method of averaging an image by itself is the linear filter. By linear filter the intensity values of pixels, within the small region of an image, are averaged using the intensity values of their neighboring pixels. The weighting and size of the filter can be adjusted to remove different types of noise (Zheng and Sun, 2008a). Generally, linear filters include a high-pass filter (Gradient and Laplacian) and a low pass filter (smoothing and Gaussion). Median filter, a nonlinear filtering technique, is another popular filter. Like the low-pass filtering, median filtering smoothes the image and is thus useful in reducing noise. Unlike low-pass filtering, median filtering can preserve discontinuities in a step function and can smooth a few pixels whose values differ significantly from their surroundings without affecting the other pixels. Median filter is often applied to gray value images due to its property of edge preserving smoothing (Kosechan and Abidi, 2001). It is also known as bilateral filter, originally proposed by Tomasi and Manduchi (1998), was employed by Du *et al.* (2008) as a heuristic tool for noise removal in beef images. Du and Sun (2004) used a median filtering method to remove possible noises within a pizza base image and reported that the median filter replaced the output pixel with the median of its neighboring pixel values instead of a weighted sum of those values that helped in the thresholding-based segmentation of pizza images. Labbafi *et al.* (2007) applied a median filter, to remove impulse noise and to close the interfaces thereby preserving the edges and contours, and developed an on-line optical method for the assessment of the bubble size and the morphology of aerated food products.

There are 2 primary advantages of great use of the median filter in the food industry (Du and Sun, 2004; 2006a; Faucitano *et al.,* 2005): it does not shift the edges of an image, as may occur with a linear filter (Russ, 1999), and noise removal does not reduce the difference in brightness of images. In addition, this technique can be considered as a special case for filters called rank statistic filters, allowing the edges to be preserved while filtering out the peak noise. For that reason, the median filter is often used before applying an edge detection technique. Leemans *et al.* (1998) used 2 types of filters: a '3x3 median filter' and a '3x3 box filter' for segmenting defects on 'Golden Delicious' apples to preserve the main apple defect as much as possible. Goodrum and Elster (1992) applied the 'filter factor', namely, the modified unsharp filter transform, which is a Laplace transform of an image added to the same image, to enhance cracks in an egg image without overly enhancing other surface features and noise. Bennedsen *et al.* (2005) identified defects in images of rotating apples using images taken with 740- and 950-nm filters to eliminate false positives reportedly caused by shadows; in earlier investigations sets of interferometric filters had been applied to analyze variations in light intensity, as recorded by a black-and-white video camera. Thus, a filter can be used to discard those images which add little or no information to the system (McNitt-Gray *et al.*, 1995) and to focus the attention of the machine vision system on the same phenomenon being visually observed.

3.1.2.2 Contrast Enhancing

Contrast generally refers to the difference in luminance, or grey level values, in an image and is a most important characteristic of an image. Sometimes images captured are of low contrast: the intensity values of the images are within a small range of intensity levels, and thus pixels with different intensity values are not well distinguished from each other. The process to increase the difference in intensity values among pixels, so that they can be effortlessly distinguished by human or computer vision is known as contrast enhancing.

Two definitions have been commonly used for measuring the contrast of the test targets. One is Michelson formula [Eq. (1)], used to measure contrast of a periodic pattern such as a sinusoidal grating and other is Weber fraction [Eq. (2)], used to measure the local contrast of a single target of uniform luminance seen against a uniform background.

$$C = \frac{L_{\max} - L_{\min}}{L_{\max} - L_{\min}} \quad (1)$$

$$C = \Delta L / L \quad (2)$$

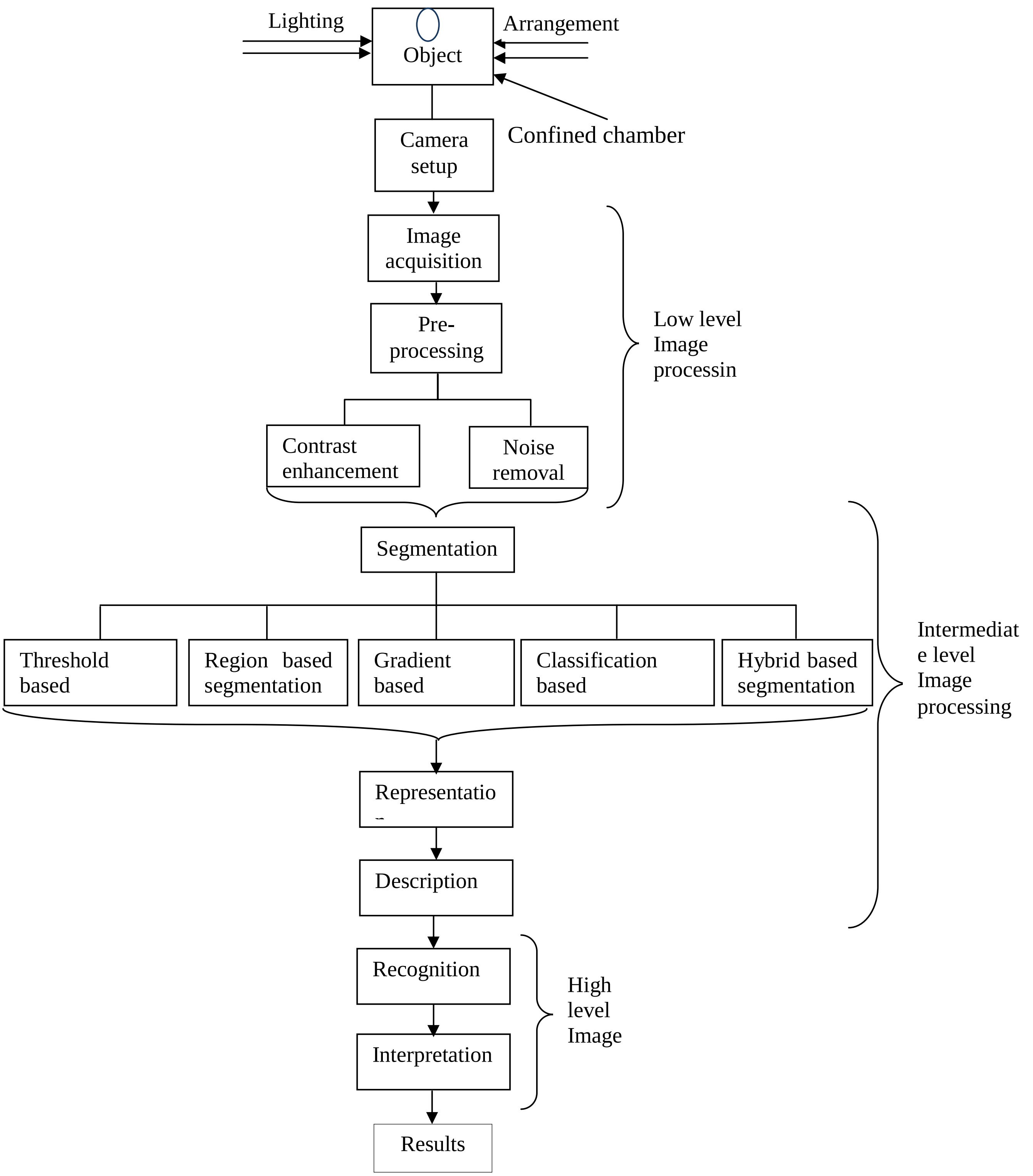

Fig 1b: Various steps of low-, mid- and high-level image processing techniques

where L_{max} and L_{min} are the maximum and minimum luminance values, respectively, in the gratings and ΔL is the increment or decrement in the target luminance from the uniform background luminance L (Peli, 1990). The contrast ratio has a strong bearing on the resolving power. The larger this ratio, the more easy it is to interpret the image (Bagade and Shandilya, 2011).

Histogram scaling and equalization are 2 popular contrast enhancement techniques. Histogram equalization is the most utilized technique in the food industry for contrast enhancing of images (Jain, 1989). In this technique, a histogram of the original image is redistributed to produce a uniform population density, which is obtained by grouping certain adjacent grey values and by spreading out the number of pixels at the histogram peaks, thereby selectively compressing those at the histogram valleys (Gauch, 1992; Bagade and Shandilya, 2011). In contrast, in histogram scaling the original histogram is transferred from one scale to another (mostly from smaller to larger). The histogram scaling function can be linear or nonlinear and also can be one-to-one or multiple-to-one. Most of the transform functions for histogram scaling are limited to proposed cases.

Histogram equalization is operated on an image in 3 steps: histogram formation, new intensity value calculations for each intensity level, and replacement of the previous intensity values with the new intensity values (Bagade and Shandilya, 2011). A contrast limited adaptive histogram equalization method was developed by Du and Sun (2006a) and applied to adjust pork images by facilitating the segmentation of pores. In this method, they enhanced the contrast of the images by dividing each image into nonoverlapping small regions and then enhancing the contrast in each small region. So, by enhancing image contrast, the accuracy of the image processing system could be improved and lead to success of image analysis (Gunasekaran, 1996).

3.1.3 Mid-Level Processing-Segmentation Techniques

Mid-level processing involves image segmentation and image representation and description. Segmentation of food images, which refers to automatic recognition of food products in images, is of course required after image acquisition, because food quality evaluation is completely and automatically conducted by computer programs, without any human participation in computer vision techniques (Zheng and Sun, 2008a). The segmentation techniques allow partitioning of images into regions that have a strong correlation with objects or areas of interest, as shown in Fig 1b. As the subsequent extracted data are highly dependent on the accuracy of image segmentation, this operation is one of the most important steps in the entire image processing technique (Sonka *et al.*, 1999; Sun, 2000) and also most difficult tasks in image processing (Harrabi and Ben Braiek, 2011). A large number of segmentation techniques have been developed. Of these, thresholding-based, region–based, gradient-based, and classification-based segmentations are the 4 most popular techniques in the food industry (Zheng and Sun, 2008a). However, until now there is no general technique that can solve all the different image segmentation type (Harrabi and Ben-Braiek, 2011).

3.1.3.1 Thresholding-Based Segmentation

Thresholding is a technique frequently applied to image segmentation and widely used in many image processing applications such as medical image processing (Yan *et al.*, 2005), detection of video change (Jing *et al.*, 2005), optical color recognition (Shaha and Udupa, 2001), food processing, etc. It chooses proper threshold nT to divide the image pixels into several classes and separate the objects from background (Kaur and Kaur, 2011). However, the fundamental principle of thresholding technique is based on the characteristics of image. This technique can be divided into bi-level and multilevel category. In bi-level thresholding, a threshold is determined to segment the image into two brightness regions which correspond to background and objects while in multilevel thresholding, more than on threshold will be determined to segment the image into certain brightness regions which correspond to one background and several objects (Huang *et al.*, 2005). Several methods have been proposed to automatically select the threshold such as two dimensional entropy (Abutaleb, 1989), through moment preservation technique (Tsai, 1985), maximizing of nonfuzziness of the 2D grayscale histogram (Wang *et al.*, 2002), discriminant analysis or variance based (Otsu, 1979), etc. used in bi-level thresholding. The methods of thresholding based on distribution function (Boukharouba *et al.*, 1985), quad-tree approach which combines both statistical and spatial information (Spann and Wilson, 1985), hill-clustering (Papamarkose and Gatose, 1994), connectivity preservation criteria (O'Gorman, 1994), verification based multi threshold probing scheme (Jiang and Mojon, 2003), etc. are used in multilevel thresholding.

Further, thresholding can be divided into global, local and dynamic thresholding techniques (Kaur and Kaur, 2011). However, only global thresholds (fixed value) are used in practice, known as bi-level and tri-level thresholding. The 4 main methods for the selection of the global thresholding are manual, isodata (Ridler and Calvard, 1978), objective function, and histogram clustering. Among these, manual selection is not ideal for online automatic food quality evaluations using computer vision. Ridler and Calvard (1978) developed the first automatic threshold selecting method, namely the isodata algorithm. The objective function method can be used alternatively. Variance-based (Otsu, 1979) and entropy-based (Pun, 1980; Kapur *et al.,* 1985; Sahoo *et al.,* 1997) are the 2 kinds of objective functions that are used mostly. Among these, Otsu's method is referred to as one of the most powerful methods for bi-level thresholding application (Sahoo *et al.,* 1998). Otsu method can provide satisfactory results even in the case of unimodal histogram images which do not have two obvious peaks and can be used as a classical method in real thresholding application (Cao *et al.,* 2002). For gray level gray level image $f(x,y)$, Otsu (or bi-level) thresholding is used to transform $f(x,y)$ to binary image $g(x,y)$ by a threshold T which can be expressed as:

$$g(x,y)=\begin{cases}0, & if\ f(x,y)\le T\\ 1, & otherwise\end{cases}$$

However, using the Otsu's technique alone uneven lighting gray level images cannot be thresholded accurately and effectively. Huang *et al.* (2005) have a method for thresholding in partitioned windows based on pyramid data structure manipulation with window size adoptively selected according to Lorentz information measure to solve the problem of uneven lighting and reported that to emphasize the partitioned windows technique, only Otsu's thresholding method was considered. Since, Otsu's technique can be easily extended to other bi-level and multilevel thresholding. So, multilevel thresholding can be considered an extension of bi-level thresholding in which a gray level image $f(x,y)$ is transformed to a multilevel image $g(x,y)$, by several thresholds T_1, $T_2 \ldots\ldots, T_m$, as:

$$g(x,y)=\begin{cases}0 & if \quad f(x,y)\le T_1\\ 1 & if \quad T_1 < f(x,y)\le T_2\\ . & \\ . & \\ m & if \quad f(x,y) > T_m\end{cases}$$

Clustering is an example of multiclass thresholding and the methods entropy, metric, moments, and interclass variance is reserved for strictly binary thresholding techniques. Based on bi-level thresholding method, Teoh and Syaifudin (2007) discriminated mango object from the background of filtered mango image during processing and analysis of image for estimating weight of Chokanman mango. Bulanon *et al.* (2001) used multivariable thresholding to develop a machine vision system to guide the developed robotic hand and found that 80% of the apples segmented using two color models (LCD and chromaticity). A new method 'reduced−dimension clustering (RDC)' was developed by Steward *et al.* (2004) for segmentation of vegetation and reported that the segmentation performance was consistently high, with average segmentation success rates of 89.6% and 91.9% across both cloudy and sunny lighting conditions, respectively.

In addition, Panigrahi *et al.* (1995) have developed an automatic thresholding technique to segment the background from the images of corn germplasm and found that the modified Otsu algorithm performed better than the no modified Otsu algorithm. The variance-based objective function generally performs better than the entropy-based one, except for images in which the population of one class is relatively larger than that of the other (Read, 1982). But when the population of one class over the other is lower than 0.01, the variance-based objective function produces erroneous results (Kittler and Illingworth, 1986). The histogram clustering (k-means clustering) method is mainly used in threshold selection. In this method, an intensity value from l to L is picked as the threshold to segment the histogram into 2 classes, object and background, with mean intensity values (Zheng and Sun, 2008a). In spite of the techniques described above, other thresholding-based techniques used are the window extension method (Hwang *et al.,* 1997), and fuzzy thresholding technique (Tobias and Seara, 2002). Sometimes, only the thresholding technique is not enough to segment an image because the contrast of objects varies within the image. So, other techniques can be used to convert the image first and then segment the processed image with thresholding. Based on the reference image of an apple, Li and Wang (1999) developed a method to accomplish defect segmentation for a curved fruit image. In their work, they generated a reference fruit image and normalized it to achieve the original fruit image for inspection. Subtracting the normalized original fruit image from the normalized reference fruit image an image was obtained, and then they extracted defects by applying a simple thresholding method. However, it was difficult to detect defects in apple surfaces using any simple global threshold segmentation algorithm, except for adaptive thresholding methods (Li *et al.,* 2002).

3.1.3.2 Region-Based Segmentation

Region-based segmentation methods are usually proposed for segmenting complex images in which the number of classes is large and unknown. However, region-based methods are less popular in the applications of computer vision in the food industry. Generally, there are 2 region based-segmentation techniques: growing-and-merging (GM), and splitting-and-merging (SM) (Navon *et al*., 2005). In GM, neighboring pixels iteratively are merged into the pixel, selected as a growing region, until no more pixels can be merged. Afterwards, the growing procedure is repeated with another pixel that has not been merged into any regions, unit all the pixels in the image have been merged into various regions to find out regions that are too small to remain as independent, mostly due to the presence of noise. In other words GM is a bottom-up method that groups pixels or subregions into larger regions according to a set of homogeneity criteria (Du and Sun, 2004). Sun and Du (2004) proposed a GM algorithm for the segmentation of pizza toppings which is impossible by thresholding-based methods. They reported that the region-based segmentation methods are less popular in the application of computer vision in the food industry and have limited instances of use, except GM.

In the SM method, the whole image is initially regarded as a big region, and is split iteratively into smaller regions with uniform image characteristics (such as color, gradient, and texture). In other words, SM is a top-down method that successively divides an image into smaller and smaller regions until certain criteria are satisfied (Du and Sun, 2004). Yang (1994) developed a flooding algorithm, a region-based segmentation method, to detect apple surface features by introducing the concept of topographic representation. In their study they treated detection of the patch-like features as one of catchment-basin detection in apple grey-level landscapes and reported that, after the flooding process, the catchment basins became lakes for which geometric parameters such as area and perimeter can be easily extracted. Sun (2000) developed a new region-based segmentation algorithm for processing pizza images. It employs the traditional region-based segmentation as a dominant method and combines the strengths of both thresholding and edge-based segmentation techniques. This new algorithm adopted a scan-line-based growing mode instead of the radial growing mode employed in a traditional region growing algorithms. First, it partitioned a pizza image into horizontal or vertical lines after edge detection, and then merged the lines into small homogeneous regions. Finally, the small regions were merged into larger regions that represent topping objects.

Region-based algorithms are computationally more expensive than the simpler techniques, such as thresholding-based segmentation, but region-based segmentation is able to utilize several image properties directly and simultaneously in determining the final boundary location. It shows the greatest promise in the segmentation of food products because strong prior knowledge is not available.

3.1.3.3 Gradient-Based Segmentation

The thresholding approach accomplishes segmentation by partitioning the image into sets of interior and exterior points. By contrast, gradient-based approaches attempt to find the edges directly by their high gradient magnitudes. Gradient-based segmentation method is similar to edge detection based on the gradient of an image (Du and Sun, 2004). Computing the image gradient is favored simply because boundaries of local contrast can be effortlessly observed in the gradient images, thus edges of the objects can also be easily detected. Image segmentation is meanwhile accomplished, since the edges of objects in images are located. Therefore, gradient-based segmentation is also called “edge detection.” Edge-based segmentation relies on edge detection by convolute edge operators (Jain, 1989). Considering the image as a function f of the intensity value of pixels (x, y), the gradient g can be computed by:

$$g = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2} \quad (2)$$

In a digital image, a gradient operator is similar to an averaging operator (for noise removal). Some of the well-known gradient operators that have been widely used are Sobel, Prewitt, Roberts, and Kirsch operators (Russ, 1999). Although most of these operators are competent when the intensity transition in images is very abrupt; and as the intensity transition range gradually gets wider and wider, the gradient operators might not be as effective as they are supposed to be. So, the second-order derivative operators are depicted as alternative approaches by researchers for gradient operators as:

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \quad (3)$$

The Laplace operator is one of the more widely used derivative operators in which the second- order derivative is determined by subtracting intensity values of the neighboring pixels from the value of the central pixel (Marr and Hildreth, 1980). However, these operators have not yet seen employed in the food industry.

The Canny edge detector, widely used in the food industry for boundary extraction of food products, performs maximum suppression of false responses including the assessment of the optimal signal-to-signal and optimal locality (Canny, 1986). The active contour model (ACM) is another popular gradient-based technique and is known as “Snakes,” which transforms the problem of edge detection into an energy optimization (Zheng and Sun, 2008a). The ACM method can be used for the segmentation of touching adjacent rice kernels (Wang and Chou, 1996). Jia *et al.* (1996) used image segmentation algorithms involving edge detection and boundary labeling and tracking to locate the position of whole fish. A Canny edge detector with Gaussian smoothing parameter 1.0 was selected to obtain the fish edge image and a labeling and tracking algorithm based on a recursive procedure was developed for locating, tracking, and thinning the fish boundary. However, the application of the gradient-based segmentation is limited because completed boundaries are difficult and sometimes impossible to trace in most food images. Edge operators detect discontinuities in grey level, color, texture, and so on. Region segmentation involves the grouping together of similar pixels to form regions representing single objects within the image.

3.1.3.4 Classification-Based Segmentation

Classification-based segmentation is the second most popular method, after thresholding-based segmentation, used in the food industry. It is a pixel-oriented and each pixel is regarded as being an independent observer whose variables are generally obtained by image features (such as color, shape, and texture). Afterwards, a matrix that contains every pixel as an observer is obtained as the input for classification. Each observer is then classified (object and background, or defect and nondefect, and so on) according to its variables, using a learning model (Du and Sun, 2006b).

Furthermore, features like extraction technique have drawn strong interest from researchers carrying out work on apple quality evaluations using computer vision technology (Kleynen *et al.*, 2005). Sometimes, to acquire more information about a pixel, its feature can be extracted from a small region that is centered on the pixel. Therefore, besides the intensity value, the image texture, which is an important factor of the product surface for pattern recognition due to its powerful discrimination ability (Amadasun and King, 1989), can also be extracted as a classification feature of pixels.

Since a large amount of data is present in the input matrix for classification, it is generally preferred that the dimension of the original matrix is reduced before classification. Accordingly, a self-organizing map (SOM) has been developed and generalized by extracting the intrinsic topological structure of the input matrix from the regularizations and correlations among observers. Afterwards, the SOM can be used for classification rather than the original observers, and the observers are assigned to the class of the neuron that the observers belong to (Chtioui *et al.*, 2003; Marique *et al.*, 2005).

Classification-based methods attempt to assign each pixel to different objects based on classification techniques like statistical, fuzzy logic, and neural network methods (Du and Sun, 2004). A Bayesian classification process was used successfully to segment apple defects (Leemans *et al.*, 1999). In this process, the color frequency distributions of the healthy tissue and of the defects were used to estimate the probability distribution of each class. The results showed that most defects could be segmented by this method, although russet was sometimes confused with the transition area between ground and blush color. In addition to this, fuzzy clustering can be used to simulate the experience of complex human decisions and uncertain information (Chtioui *et al.*, 2003; Du and Sun, 2006b). In spite of the above discussion, an important caveat is that classification-based segmentation methods lack a structured way for coping with variations in rotation and scale, which limits their applicability (Du and Sun, 2004).

3.1.3.5 Other Segmentation Techniques

Although a large number of segmentation techniques have been developed to date, no universal method can perform with ideal efficiency and accuracy across the infinite diversity of imagery (Bhanu *et al.*, 1995). So, we must develop and combine several techniques in order to improve the segmentation results and increase adoptability of the methods. Watershed and hybrid-based segmentation techniques are more popular. For instance, Hatem *et al.* (2003) developed an algorithm with an accuracy of 83% for the segmentation of cartilage and bone in images of vertebrate animals by using a thresholding-based method twice. The concept of watersheds, which are introduced into digital images for morphological processing, originally comes from topography. The watersheds can be constructed from different scales of images – grayscale (Vincent and Soille, 1991), binary (Casasent *et al.*, 2001), and gradient (Du and Sun, 2006a). Owing to the presence of noise and local irregularities, there are far more minima from which far more catchment basins are formed, causing an over-segmentation of images. To overcome this problem, algorithms are assigned. One method for preventing over-segmentation of images is to eliminate the undesired minima, using morphological operators such as opening and closing. One such method was proposed by Du and Sun (2006a) to segment pores in pork ham images. In other methods, post-processing is conducted to merge over-segmented regions with similar image characteristics. Such a method with a graphic algorithm to determine the similarity of merging neighboring regions was developed by Navon *et al.* (2005).

Despite all this, because image segmentation is by nature still an ill-defined problem, none of the methods described can perform ideally across diverse images. It has been suggested recently that several techniques might be combined together for the sake of improving the segmentation result and simultaneously increasing segmentation speed (Zhen and Sun, 2008a).

3.1.4 High-Level Processing: Image Analysis

After image segmentation, where objects are discriminated from the background, the characteristics of the objects, known as object measurements, are calculated. These measurements are the core elements in a computer vision system, because they contain useful information for image understanding and interpretation and for object classification (Ballard and Brown, 1982). Interaction with a knowledge database at all stages of the entire process is essential for more precise decision-making and is seen as an integral part of the image processing process. The operation and effectiveness of intelligent decision making is based on the provision of a complete knowledge base, which in machine vision is incorporated into the computer. Algorithms such as neural networks, fuzzy logic, and genetic algorithms are some of the techniques of building knowledge bases into computer structures. Such algorithms involve image understanding and decision-making capacities, thus providing system control capabilities. Neural network and fuzzy logic operations have been implemented successfully with computer vision in the food industry (Ying *et al.*, 2003). High-level processing involves recognition and interpretation, typically using statistical classifiers or multilayer neural networks of the region of interest. These steps provide the information necessary for the process/machine control for quality sorting and grading (Brosnan and Sun, 2004). For instance, measurements such as size, shape, color, and texture are carrying direct information and can be used in quality evaluations and inspection tasks. These measurements are rated as the primary object measurements, can be acquired from images (Du and Sun, 2004). Although a number of methods have been developed over the past few decades, there is not yet a perfect method for each type of measurement, and especially for texture measurements because of the lack of a formal and scientific definition of image texture while facing infinite diversity of texture patterns (Zheng *et al.*, 2006a).

3.1.4.1 Artificial Neural Network Based Food Classification

An artificial neural network consists of a pool of simple processing units which communicate by sending signals to each other over a large number of weighted connections. ANN is a technique for solving problems by constructing software that works like our brains. The application of artificial neural networks (ANNs) in the food science have been emerged from the last two decades and this technique is very useful for the analysis and modeling of food quality and safety. Although, most applications of ANNs are in the development stage, the prediction of food safety and quality (physical, chemical, functional and sensory properties) of various food products during processing and distribution, and spectroscopic data interpretation using ANNs are going to be popular (Huang *et al.*, 2007).

Nakano *et al.* (1992) have developed three (27 units in input, 10 units in hidden and 3 units in output) layers ANN to classify apples based on external appearance. Similarly, Nakano (1997) graded apples into ‘superior’, ‘excellent’, ‘good’, ‘poor colour’, and ‘injured’ based surface color by applying ANN model. In another study by Kavdir and Guyer (2002), Empire and Golden Delicious apples were sorted based on their surface quality conditions using back propagation neural networks. Pixel gray values and texture features obtained from the entire apple image were used as input to artificial neural network classifiers. Kavdir and Guyer (2004) compared Artificial Neural Networks and Statistical Classifiers in apple sorting using textural features and reported that histogram features were significantly lower than the other classification applications, the BPNN using textural features performed 93·8% success rate in recognizing Empire apples. However, for Golden Delicious apples, all the classifiers produced similar accuracy rates ranging between 85·9 and 89·7%.

Similarly, multi-structure neural network (MSNN) classifier, consisted of four parallel discriminators, for classification of four classes of pistachio nuts was developed by Ghazanfari *et al.* (1996) and compared with the performance of a multi-layer feed-forward neural network (MLNN) classifier, the average classification accuracy of MSNN classifier was 95.9%, an increase of over 8.9% of the performance of MLNN. Neural network, in addition, has also been used to classify poultry carcass (Park, 1996; park and Chen, 2000), vegetables (Brandon, 1990; Shahin *et al.,* 2002) and cereal grains (Paliwal *et al.,* 2001; Luo *et al.,* 1999).

3.1.4.2 Fuzzy Logic Based Food Classification

The word Fuzzy can be defined as “not clear, distinct, or precise; blurred” (Bih, 2006). Similarly, Fuzzy logic is a form of knowledge representation suitable for notions that cannot be defined precisely, but which depend upon their contexts (Rekiek and Delchambre, 2006). It provides an alternative way to represent linguistic and subjective attributes of the real world in computing and use to control systems and other applications in order to improve the efficiency and simplicity of the design process (Nicy *et al.,* 2014; Sethia *et al.,* 2013). Three steps i.e. fuzzification, fuzzy inference and defuzzification, are required for the implementation of fuzzy logic in to a real word (Murthy and Biswas, 2004).

Fuzzification converts classical data or crisp data into fuzzy data or Membership Functions (MFs). In practice, membership functions can have multiple different types, such as the triangular waveform, trapezoidal waveform, Gaussian waveform, bell-shaped waveform, sigmoidal waveform and S-curve waveform. The exact type depends on the actual applications. For those systems that need significant dynamic variation in a short period of time, a triangular or trapezoidal waveform should be utilized. For those system that need very high control accuracy, a Gaussian or S-curve waveform should be selected. The core of a fuzzy set is the set of elements whose degree of membership in that set is equal to 1, which is equivalent to a crisp set. The boundary of a fuzzy set indicates the range in which all elements whose degree of membership in that set is between 0 and 1 (0 and 1 are excluded). After the membership functions are defined for both input and output, the next step is to define the fuzzy control rule by using fuzzy inference process (FIP). The FIP combine membership functions with the control rules to derive the fuzzy output. At last, in the defuzzification each associated output is calculated and put them into a table (the lookup table) by using different methods. Since, the fuzzy conclusion or output is still a linguistic variable, and this linguistic variable needs to be converted to the crisp variable via the defuzzification process. The defuzzification process is meant to convert the fuzzy output back to the crisp or classical output to the control objective. For this purpose, three defuzzification techniques (Mean of Maximum method, Center of Gravity method and the Height method) are commonly used. However, with the rapid development of fuzzy technologies, later on different fuzzy control strategies have been developed based on different classical control methods, such as PID-fuzzy control, sliding-mode fuzzy control, neural fuzzy control, adaptor fuzzy control and phase-plan mapping fuzzy control. In addition, more and more new fuzzy control strategies or combined crisp and fuzzy control techniques are being developed and will be applied to many areas in our society in the future. Furthermore, the law to design or build a set of fuzzy rules is based on a human being’s knowledge or experience, which is dependent on each different actual application. A fuzzy IF-THEN rule associates a condition described using linguistic variables and fuzzy sets to an output or a conclusion. The IF part is mainly used to capture knowledge by using the elastic conditions, and the THEN part can be utilized to give the conclusion or output in linguistic variable form. This IF-THEN rule is widely used by the fuzzy inference system to compute the degree to which the input data matches the condition of a rule. Two types of fuzzy control rules are widely utilized for most real applications. One is fuzzy mapping rules and the other is called fuzzy implication rules. Fuzzy mapping rules provide a functional mapping between the input and the output using linguistic variables. The foundation of a fuzzy mapping rule is a fuzzy graph, which describes the relationship between the fuzzy input and the fuzzy output. Fuzzy mapping rules work in a similar way to human intuition or insight, and each fuzzy mapping rule only approximates a limited number of elements of the function, so the entire function should be approximated by a set of fuzzy mapping rules.

Fuzzy classification methods have now been used widely in the field of agriculture and its allied sectors. For instance, in the field of food process for automatic grading of fish products (Hu *et al.,* 1998), rating of tomatoes (Jahns *et al.,* 2001), classifying of pizza (Sun and Brosnan, 2003a; 2003b), sensory evaluation of coffee (Lazim, Suriani), etc.

4. Conclusion

In this paper, image processing tools and techniques used in computer vision are reviewed based on 5 important image processing steps. A variety of image processing techniques have been used to perform food quality evaluations with various degrees of success. Three image pre-processing methods, low, medium, and high processing, can be utilized to improve the quality of an image for further processing. Thresholding-based, gradient-based, region-based, and classification-based approaches are the 4 main techniques applied to segment food products. Furthermore, size, shape, color, and texture are the 4 most common classes used to measure object features in a food product image. In addition, the methods fuzzy logic and neural network are currently employed to perform classification. Fuzzy classification uses fuzzy logic concepts and neural networks simulate biological nervous systems.

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