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Review

Recent developments in the applications of image processing techniques for food quality evaluation

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Image processing techniques have been applied increasingly for food quality evaluation in recent years. This paper reviews recent advances in image processing techniques for food quality evaluation, which include charge coupled device camera, ultrasound, magnetic resonance imaging, computed tomography, and electrical tomography for image acquisition; pixel and local pre-processing approaches for image pre-processing; thresholding-based, gradient-based, region-based, and classification-based methods for image segmentation; size, shape, colour, and texture features for object measurement; and statistical, fuzzy logic, and neural network methods for classification. The promise of image processing techniques for food quality evaluation is demonstrated, and some issues which need to be resolved or investigated further to expedite the application of image processing technologies for food quality evaluation are also discussed.

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Introduction

In the food industry, some quality evaluation is still performed manually by trained inspectors, which is tedious, laborious, costly and inherently unreliable due to its subjective nature. Increased demands for objectivity, consistency and efficiency have necessitated the introduction of computer-based image processing techniques. Recently, computer vision employing image processing techniques has been developed rapidly, which can quantitatively characterize complex size, shape, colour and texture properties of foods. Image processing systems play a more and more important role in the food quality evaluation by maintaining accuracy and consistency while eliminating the subjectivity of manual inspections. They offer flexibility in application and can be reasonable substitutes for the human visual decision-making process.

In order to develop an automated system for food quality evaluation, image processing techniques are often combined with mechanical and instrumental devices to replace human manipulative effort in the performance of a given process. In such a system, the image processing system is the centre, which controls the operation of the machinery. Li, Wang, and Gu (2002) developed an automated system for apple surface defect detection, which consisted of a feeding unit, an apple uniform spacing unit, a machine vision system, and a sorting conveyor. The apples were fed to the machine vision system for the defect inspection with the feeding and uniform spacing conveyors, and graded with the sorting unit. Mechanization is a remaining challenge in applying machine vision for food quality evaluation, especially for those easily bruised and marked when they are in contact with hard surfaces. This paper will focus on the image processing techniques. The mechanical techniques for handling and packaging will not be discussed in detail here, interested readers can refer to the papers and books on this topic for details.

The application potential of image processing techniques to the food industry has long been recognised (Tillet, 1990). The food industry ranks among the top ten industries using image processing techniques (Gunasekaran, 1996), which have been proven successful for the objective and non-destructive evaluation of several food products (Timmermans, 1998). The basic theory of computer vision technology for food quality assurance had been reviewed by Gunasekaran (1996). The main thrust of this paper is to summarise the recent advances in the applications of image processing techniques for food quality evaluation. Image processing analysis generally consists of the following five steps as shown in Fig. 1, which are (1) image acquisition operations to convert images into digital form; (2) pre-processing operations to obtain an improved image with the same dimensions as the original image; (3) image segmentation operations to partition a digital image into disjoint and non-overlapping regions; (4) object measurement operations to measure the characteristics of objects, such as size, shape, colour and texture; and (5) classification operations to identify objects by classifying them into different groups. The aim of this paper is to review these approaches, illustrate their role in the food quality evaluation, and discuss the remaining challenges. Although this paper focuses on food quality evaluation, the techniques discussed are of relevance to the wider research topic of image processing.

Image acquisition

Illumination is an important prerequisite of image acquisition for food quality evaluation. The quality of captured image can be greatly affected by the lighting condition. A high quality image can help to reduce the time and complexity of the subsequent image processing steps, which can decrease the cost of an image processing system. Different application may require different illumination strategy. Novini (1990) reported that most lighting arrangement could be grouped as one of followings: front lighting, back lighting, and structured lighting. By enhancing image contrast, a well-designed illumination system can improve the accuracy and lead to success of image analysis (Gunasekaran, 1996).

Image acquisition, that is capture of an image in digital form, is obviously the first step in any image processing system. During the last decades, considerable amount of 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. In recent years there have been attempts to develop non-destructive, non-invasive sensors for assessing composition and quality of food products. Various sensors such as charge coupled device (CCD) camera, ultrasound, magnetic resonance imaging (MRI), computed tomography (CT), and electrical tomography (ET) are used widely to obtain images of food products.

CCD camera

CCD camera is frequently employed by the image processing systems for food quality evaluation. CCD cameras can convert light into electrical charges and create high-quality, low-noise images with lots of pixels and excellent light sensitivity, which are free of geometric distortion and highly linear in their response to light. Recently, fishery, fruit, grain, meat, vegetable, and other food quality evaluation have provided many actual and potential applications of the CCD camera. Among the applications, CCD camera was widely used for quality classification, physical characteristic detection, and property estimation of food products. Table 1 summarizes broad applications of CCD cameras for food quality evaluation. In some cases, it is difficult to evaluate food quality in ordinary spectral region. Through the use of different filters fitted to CCD cameras, analysis of images from particular spectral regions can be performed. In the research by Rigney, Brusewitz, and Kranzler (1992), a 400–620 nm interference filter was fitted to a CCD camera to examine contrast between defect and good asparagus tissue. To achieve a basically complete inspection of food products, it is necessary to use more than one camera to obtain food images from different direction. Park, Chen, and Nguyen (1998) implemented a multi-spectral imaging technique with four 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 of apple surface defect based on computer image technology. Two CCD cameras, with interference band-pass optical filters (840 nm), were mounted above and below the conveyor.

Acquisition technology for internal structures

External attributes such as size, shape, colour, surface texture and external defects can be evaluated by ordinary means (e.g. CCD camera). However, internal structures are difficult to be detected with relatively simple and traditional imaging means, which cannot provide enough information for detecting internal defects, such as water-core, internal breakdown, and hollow heart. It is necessary to apply special image acquisition techniques for food quality evaluation. Ultrasound, MRI, CT,

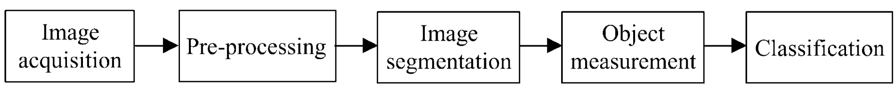

Fig. 1. Common image processing system configuration including the five components: image acquisition, pre-processing, image segmentation, object measurement, classification.

Table 1. Summary of CCD camera applications for food quality evaluation

Category	Products	Applications	References
Fishery	Bivalve	Study of larval growth	Pontual *et al.* (1998)
	Crassostrea	Detection of hinge lines	Jung and Fred (2002)
	Fish	Sorting fish	Zion *et al.* (1999)
Fruit	Apple	Defect segmentation	Leemans *et al.* (1999)
	Cherry	Analysing fruit shape	Beyer *et al.* (2002)
	Orange	Location and characterization of the stem-calyx area	Ruiz *et al.* (1996)
	Pistachio nuts	Detection of early split	Pearson and Slaughter (1996)
Grain	Rice	Quality classification	Wan *et al.* (2002)
	Wheat	Classification	Utku and Koksel (1998)
Meat	Beef	Using image texture features as indicators of tenderness	Li *et al.* (1999)
	Pork	Color evaluation	Lu *et al.* (2000)
	Poultry carcasses	Classification	Park *et al.* (2002)
Vegetable	Asparagus	Defect inspection	Rigney *et al.* (1992)
	Chicory	Study of visual preference	Coppenolle *et al.* (2002)
Others	Cheese	Evaluation of the functional properties	Wang and Sun (2001)
	Noodle	Influence of sprout damage on appearance	Hatcher and Symons (2000)
	Pizza	Quality evaluation	Sun and Brosnan (2003a, 2003b)
	Sausage	Estimation of sensory properties	Ioannou *et al.* (2002)

and ET technologies are potential solutions to the problem for inspecting internal attributes of food products. Applications of these three image acquisition techniques for food quality evaluation will be discussed separately below.

Ultrasound is a new technology that offers a route to acquire internal images for use in food quality evaluation. There are two modes for ultrasonic imaging of biological tissues. One is A-mode (amplitude modulation) and the other is B-mode (brightness modulation). While A-mode is one-dimensional and is limited to measuring depth of tissue, B-mode allows for characterisation of tissue with different densities. Real-time ultrasound (RTU) is a specialised version of B-mode ultrasound and has the ability to produce images of moving objects almost instantaneously. As a cost-effective and reliable method, the majority of applications of ultrasonic imaging in food quality evaluation can be found in the meat industry. Ultrasonic image analysis has been performed for measurement of fat thickness, estimation of yield, and assessment of quality of meat. Table 2 summarises ultrasound applications for meat quality evaluation.

MRI is an imaging technique primarily used to obtain high quality images of the inside of the object in two or three dimensions. Numerous publications in the literature have indicated that MRI can be used to non-invasively evaluate important quality attributes of food products. Being an analytical tool, MRI is based on the absorption and emission of energy in the radio frequency range of the electromagnetic spectrum. Generation of magnetic resonance images can be controlled by the radio frequency pulse sequence used for excitation of the nuclear spins. Selection of the optimal pulse sequence parameters can result in enhanced images, with good contrast between a region of interest and its surrounding area. In some instances, MRI research was conducted to measure moisture and its migration in food systems; other researches demonstrated the potential of using MRI to investigate physical or biological properties of food products; still some other work sought to estimate the yield. Table 3 summarizes the wide applications of MRI as an irreplaceable research tool for food quality evaluation.

CT is a non-destructive technique for capturing food images, which allows visualization of the internal features of an object. Based on the differential that exists between the rates at which the tissues in the object attenuate X-rays, the image of a thin slice of the object can be obtained using a movable X-ray source and detector assembly to accumulate data. A three-dimensional representation of the object can be made by stacking several slices of the scanned object and stored digitally and used later for evaluation. It is a proven efficient method for evaluating a cross-section of an object and has received extensive applications in the food industry. This method was used widespreadly for many food products, including fishery, fruits, meat, and vegetables. Table 4 summarises CT applications for food quality evaluation. In addition, CT can be used for detection of foreign materials in foods. Ogawa, Morita, Tanaka, Setoguchi, and Thai (1998) used a medical X-ray CT scanner as a non-destructive inspection method for the detection of selected non-metallic materials embedded in various fluids and food materials. The limitation of using X-ray linear absorption coefficients from typical CT systems is to detect certain combination of foreign materials and foodstuffs.

ET techniques for food image acquisition are becoming increasingly popular, which mainly consist of the following three sensing modalities: electrical resistant (impedance) tomography (ERT or EIT), electrical capacitance tomography (ECT), and electromagnetic inductance tomography (EMT). These methods exploit differences in the electrical properties of different materials to produce slice-images and they are relatively fast, non-destructive, and low-cost imagers. They are based on the measurement and computerised analysis of electrical resistivity, capacitances, and inductance changes of an object for ERT (EIT), ECT, and EMT, respectively. There are wide applications using ET techniques to improve the design and operation of equipment and ensure consistent and high quality of food product. Primrose and Bolton (2001) reported that ERT could be applied to determine presence of non-conducting foreign objects, in-line concentration of particular ingredients, degree of mixedness in static and batch mixers,

Table 2. Summary of ultrasound applications for meat quality evaluation

Products	Applications	References
Beef	Estimating marbling score	Brethour (1994)
	Evaluation of meat quality	Ozutsumi *et al.* (1996)
	Image texture analysis for characterizing intramuscular fat content	Kim *et al.* (1998)
	Predicting percentage of intramuscular fat	Hassen *et al.* (2001)
Mutton	Prediction of carcass characteristics	Stanford *et al.* (1995)
	Fat thickness and longissimus muscle area measure	Fernández *et al.* (1997)
Pork	Prediction of carcass characteristics	Smith *et al.* (1992)
	Carcass evaluation	Liu and Stouffer (1995)
	Estimation of carcass yield and quality	Sather *et al.* (1996)
	Estimation of the lean meat proportion	Hulsegge and Merkus (1997)
	Carcass grading	Brødum *et al.* (1998)
	Measurements of backfat and loin muscle area	Moeller and Christian (1998)
	Classification	Busk *et al.* (1999)
	Measures of fat depth and longissimus muscle area	McLaren *et al.* (1991)
	Grading carcasses	Fortin *et al.* (2003)
Poultry carcass	Measurement of breastmeat	Grashorn and Komender (1990)
	Evaluation of carcasses' merit	Miller (1996)

Table 3. Summary of magnetic resonance imaging applications for food quality evaluation

Category	Products	Applications	References
Fishery	Cod and mackerel	Effect of freeze-thawing	Nott *et al.* (1999)
Fruit	Apple	Observation of watercore loss	Clark *et al.* (1998)
		Detection of bruises	Zion *et al.* (1995)
	Strawberry	Acquiring water mobility and moisture data	Evans *et al.* (2002)
Grain	Maize	Measurement of stress cracking	Song and Litchfield (1994)
	Rice	Real time measurement of the change of moisture profile	Takeuchi *et al.* (1997)
	Wheat	Measurement of moisture distribution	Song *et al.* (1998)
Meat	Pork	Measurement of the inter-diffusion of sodium ions	Guiheneuf *et al.* (1997)
	Poultry	Estimation of poultry breastmeat yield	Davenel *et al.* (2000)
Vegetable	Courgette	Investigating internal structure and the effect of freezing	Duce *et al.* (1992)
	Potato	Sensory analysis	Martens *et al.* (2002)
Others	Cheese	Evaluation of eye formation and structural quality	Rosenberg *et al.* (1992)
	Chocolate	Measuring kinetics of the migration of lipids	Miquel *et al.* (2001)
	Confection	Observing moisture migration	Troutman *et al.* (2001)

Table 4. Summary of computed tomography applications for food quality evaluation

Category	Products	Applications	References
Fishery	Freshwater fish	Prediction of crude fat and crude protein content of fillets	Romvari *et al.* (2002)
	Salmon	Prediction of carcass composition	Rye (1991)
		Evaluation of body shape and visual fat deposits	Einen *et al.* (1998)
Fruits	Apple	Determining water content	Tollner *et al.* (1992)
	Nectarine	Evaluation of textural characteristics of exhibiting woolly breakdown	Sonego *et al.* (1995)
	Peach	Detecting internal changes	Barcelon *et al.* (1997)
		Internal quality evaluation of peaches	Barcelon *et al.* (1999)
	Tomato	Determining maturity	Brecht *et al.* (1991)
Meat	Broiler	Measurements of in vivo breast meat amount and yield	Remignon *et al.* (1997)
	Chicken	Detection of bone fragments in deboned poultry	Tao and Ibarra (2000)
	Pork	Measuring fat deposition and distribution	Kolstad (2001)

bubbles and structure in foods. EIT has been used for food temperature measurement (Nott & Hall, 1999). Potential applications for EMT techniques are where the material distribution can be characterised by either a high electrical conductivity or ferro-/ferri-magnetic behaviour, such as food inspection (Peyton *et al.*, 1999) and measurement of the moisture content of grains (Abdullah, Guan, Lim, & Karim, 2004). A simple ECT sensor has been developed to monitor the number of fruit pieces entering a canning machine (IFR, 2003). The drawback of ET is its relatively low spatial resolution.

Image pre-processing

Images captured by CCD camera, ultrasound, MRI, and CT are subject to various types of noises. These noises may degrade the quality of an image and subsequently it cannot provide correct information for subsequent image processing. In order to improve the quality of an image, operations need to be performed on it to remove or decrease degradations suffered by the image during its acquisition. The purpose of pre-processing is an improvement of the image data, which suppresses unwilling distortions or enhances some image features that are important for further processing and creates a more suitable image than the original for a specific application. Two different types of image pre-processing approaches can be identified for food quality evaluation: pixel pre-processing and local pre-processing, according to the size of the pixel neighbourhood that is used for the calculation of a new pixel. Pixel pre-processing is a simple but important image processing technique, which converts an input image into an output image in such a way that each output pixel corresponds directly to the input pixel having the same coordinates. However, local pre-processing methods use a small neighbourhood of a pixel in an input image to produce a new brightness value in the output image, which are also called filtration.

Pixel pre-processing

Pixel pre-processing may be viewed as pixel-by-pixel copying operation, except that the values are modified according to the specified transformation function. Colour space transformation is the most common pixel pre-processing method for food quality evaluation. Among the applications where colour space transformations have been used for image pre-processing, one would expect most applications to be based on HSI (hue, saturation, and intensity) colour space (Li, Tan, & Shatadal, 2001; Tao, Heinemann, Vargheses, Morrow, & Sommer, 1995). However, $L^*a^*b^*$ colour space has also been used to perform image pre-processing (Vizhanyo & Felfoldi, 2000).

HSI is an effective tool for colour image distinguishing. Usually, colour images are taken by a digital device and saved in the three-dimensional RGB (red, green, and blue) colour space. For efficient colour image processing of potatoes and apples, Tao *et al.* (1995) transformed the RGB colour space to HSI. The method of using the HSI colour system proved highly effective for colour evaluation and image processing. The vision system achieved over 90% accuracy in inspection of potatoes and apples by representing colour features with hue histograms. In another research, the saturation images were used for beef image analysis (Li *et al.*, 2001). The captured images were initially in the RGB format and they were transformed into the HSI format. Examination and preliminary analysis of the different image formats indicated that the saturation component, which gives a monochromatic image, revealed the muscle image texture most clearly. Sun and Brosnan (2003a) used HSI model to segment pizza sauce from pizza base and the light zones of pizza sauce from heavy zones by setting the HSI values in different ranges.

Some image pre-processing approaches utilise $L^*a^*b^*$ colour space, where the 'L^*' stands for a factor of brightness, the 'a^*' defines the content of red or green, and the 'b^*' indicates the content of yellow or blue. To emphasize specific features, the images can be improved by transforming the RGB colour space by weighting each channel in a different way. Vizhanyo and Felfoldi (2000) demonstrated that simple cluster analysis was not sufficient to discriminate the browning caused by disease from the natural browning of the mushroom; they reported that the transformation of RGB values to a^* and b^* colour components and the elimination of intensity gave a definitely better separation for the mushroom diseases.

Local pre-processing

Local pre-processing methods calculate the new value based on the averaging of brightness values in some neighbourhood points, which have similar properties to the processed point. The local pre-processing applications for food quality have various designs ranging from relatively straightforward to highly complex approaches. According to the specific problem, local pre-processing methods can be used to blur sharp edges, or to preserve edge in the image.

In the most basic local pre-processing approach, simple filter is used to suppress noise or other small fluctuations in the image. In the extraction of features of wheat grains, Utku and Koksel (1998) applied filter to remove possible noise within the image data. A non-linear filtering method (median filtering) was used to suppress noise. The median filter technique can be considered as a special case for filters called rank statistic filter, which allowed the edges to be preserved while filtering out the peak noise. For this reason, the median filter is often used before applying an edge detection technique. To preserve the main apple defect as much as possible, Leemans, Magein, and Destain (1998) used two types of filters: a '3×3 median filter' and a '3×3 box filter' for segmenting defects on 'Golden Delicious' apples.

For some special aims, more complex local pre-processing methods have been applied for food quality evaluation. Goodrum and Elster (1992) applied the 'filter factor', i.e. modified unsharp filter transform, which is a Laplace transform of an image added to the same image, to enhance cracks in the egg image without overly enhancing other surface features and noise. This operation, followed by a contrast stretch, produced very satisfactory results. Sensitivity to translucent spots was decreased while sensitivity to cracks was increased. So and Wheaton (1996) developed a method to smooth a binary oyster image, which includes shrink, expansion, and closing process. The shrink operation removed small objects (e.g. noise) while the expansion process filled holes and concavities in objects. Initially the shrink and expansion process was used. Then the whole binary image was further smoothed using a closing process to eliminate small objects that still existed after the shrink and expand operation, or to isolate the objects from the binary image. By filling the streak at narrow places along the streak, the closing process also split a dark convex object that intersected the image into two or more regions.

Image segmentation

Image segmentation partitions an image into its constituent objects, which is a challenging task because of the richness of visual information in the image. The techniques of image segmentation developed for food quality evaluation can be divided into four different philosophical approaches, i.e. thresholding-based, region-based, gradient-based, and classification-based segmentation. Current literature survey on image segmentation indicates that in most applications thresholding-based and region-based methods have been used for segmentation. The other two methods, i.e. gradient-based and classification-based approaches, are used less frequently.

Thresholding-based segmentation

Thresholding-based segmentation is a particularly effective technique for scenes containing solid objects resting upon a contrasting background, which distinguishes the object from the remaining part of an image with an optimal value. Among the thresholding-based segmentation methods for food quality evaluation, some perform segmentation directly by thresholding, and others combine with other techniques.

Thresholding works well if the objects of interest have uniform interior grey level and rest upon a background of different, but uniform, grey level. Zion, Chen, and McCarthy (1995) developed a method for fast and computerised detection of bruises in magnetic resonance images of apples. A computationally simple thresholding technique was used to distinguish between bright pixels representing the vascular system, and those representing bruises. Sun and Brosnan (2003a) analysed pizza sauce image based on thresholding that included three steps. Firstly the whole pizza image was segmented from the white background using the RGB model. Then by setting the HSI values in the following ranges [220, 14], [0, 125] and [0, 200], respectively, segmentation of pizza sauce from pizza base was achieved. Finally, segmentation of the light zones of pizza sauce was accomplished by setting the HSI values as follows: [2, 14], [53, 125] and [106, 200], respectively. Figure 2 shows the segmentation of an individual sample on the basis of heavy and light zones of sauce.

In some cases, only thresholding technique is not enough to segment an image because the contrast of objects varies within the image. 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

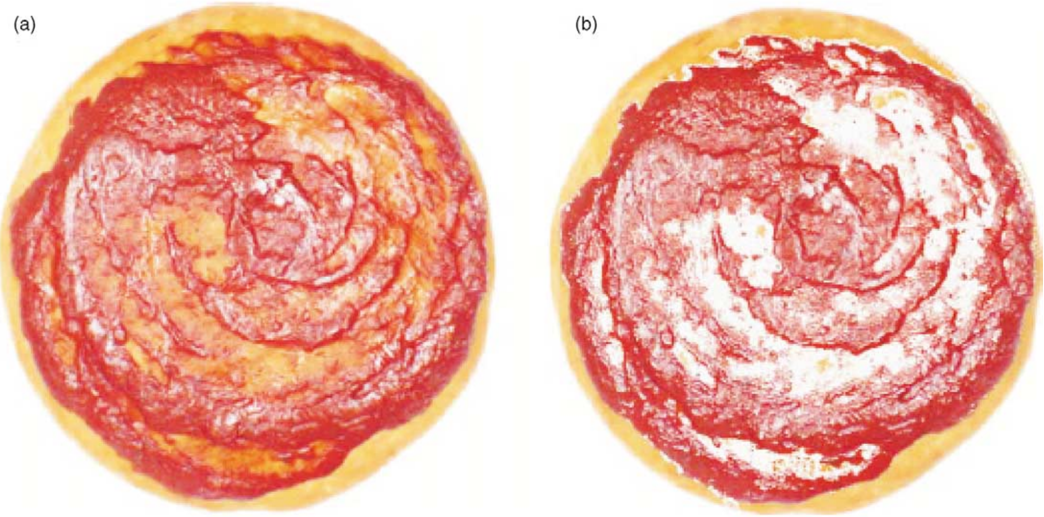

Fig. 2. Segmentation of a sample on the basis of light and heavy zones of sauce: (a) original image of even spread sample and (b) image after segmentation where white zones are the light sauce spread areas (Sun and Brosnan, 2003a).

method to accomplish defect segmentation for a curved fruit image. Firstly, a reference fruit image was generated and the normalised reference fruit image (NRFI) was then achieved by normalising the original fruit image for inspection. Secondly, an image was obtained by subtracting the normalised original fruit image from the NRFI. Finally, a simple thresholding process was applied to extract the defects. In other cases adaptive thresholding techniques can be adopted instead of a fixed global threshold to segment an image. Panigrahi, Misra, Bern, and Marley (1995) developed an automatic thresholding technique to segment the background from the images of corn germplasm, which was a modification of Otsu's algorithm (Otsu, 1979) using probability theory. It was found that the modified Otsu's algorithm performed better than the Otsu's algorithm and was successful in automatic background segmentation of corn germplasm images (Panigrahi *et al.*, 1995). The misclassification occurred with the Otsu's algorithm of exposed cob in the image as background was eliminated by this modified algorithm. For meat fillet, the simplest thresholding way to segment foreign objects in X-ray images of meat fillet often fails due to the uneven thickness of the fillet. To overcome this problem, Tao, Chen, Jing, and Walker (2001) developed an adaptive thresholding method for image segmentation, with the threshold functions resulting from smoothing X-ray images. This technique can be implemented for thickness-invariant image segmentation for the adaptiveness to local intensity level, which is proportional to the meat thickness. However, for defect detection of apple surface, it is difficult to use any simple global thresholding segmentation algorithm, and thus local adaptive thresholding methods were developed for defect segment extraction. (Li *et al.*, 2002).

Region-based segmentation

Region-based segmentation methods can be divided into two basic classes: region growing-and-merging (GM) and region splitting-and-merging (SM). The former is a bottom-up method that groups pixels or subregions into larger regions according to a set of homogeneity criteria; and the latter is a top-down method that successively divides an image into smaller and smaller regions until certain criteria are satisfied. Region-based algorithms are computationally more expensive than the simpler techniques, e.g. 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 *priori* knowledge is not available.

A region-based segmentation method, i.e. the flooding algorithm, was developed to detect the apple surface feature (Yang, 1994). By introducing the concept of topographic representation for apple images, the detection of the patch-like features was treated as one of catchment basin detection in apple grey-level landscapes. 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 the pizza images. It employed 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 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. Figure 3 shows an example of pizza images and its segmentation result using the new region-based segmentation technique developed. A method to perform segmentation of X-ray images of randomly oriented and touching pistachio nuts was also developed (Casasent, Talukder, Keagy, & Schatzki, 2001), which consisted of a fast blob-colouring algorithm combined with a new binary watershed algorithm. Using the estimates of object centres to initiate and define basins, the new watershed algorithm can overcome internal grey-scale object variations. Results of experiments carried out on different sized pistachios achieved 99.3% segmentation.

Gradient-based and classification-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. Jia, Evans, and Ghate (1996) used image segmentation algorithms involving edge detection and boundary labeling and tracking to locate the position of the whole fish. A Canny edge detector with Gaussian smoothing parameter 1.0 (Canny, 1986) 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. The algorithms are robust to noise and invariant to translation, rotation, and scaling of a catfish. However, the application of the gradient-based segmentation is limited because completed boundaries are difficult and sometimes impossible to trace in most food images.

Classification-based methods attempt to assign each pixel to different objects based on classification techniques like statistical, fuzzy logic, and neural network. A Bayesian classification process was used successfully to

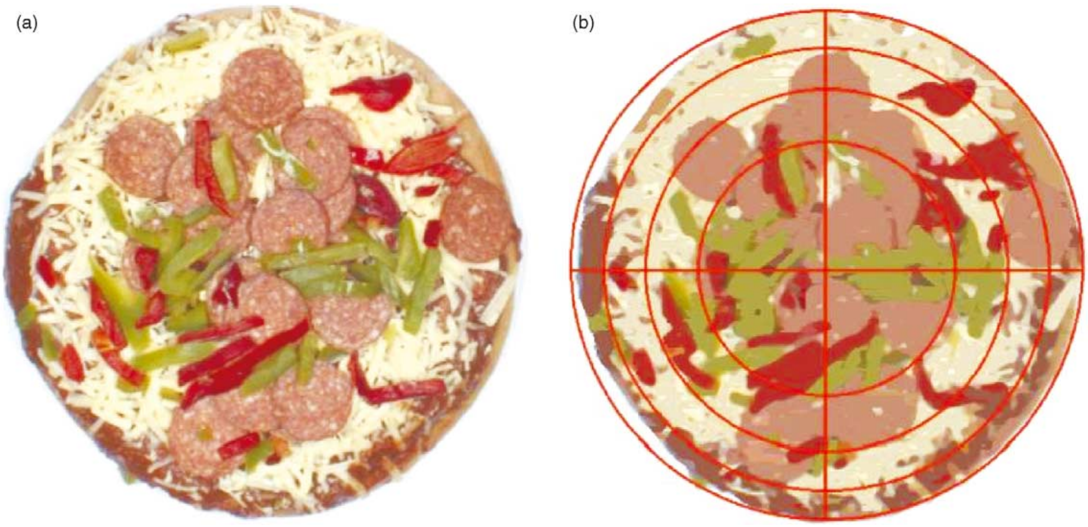

Fig. 3. Pizza images: (a) original image; (b) segmented image (Sun, 2000).

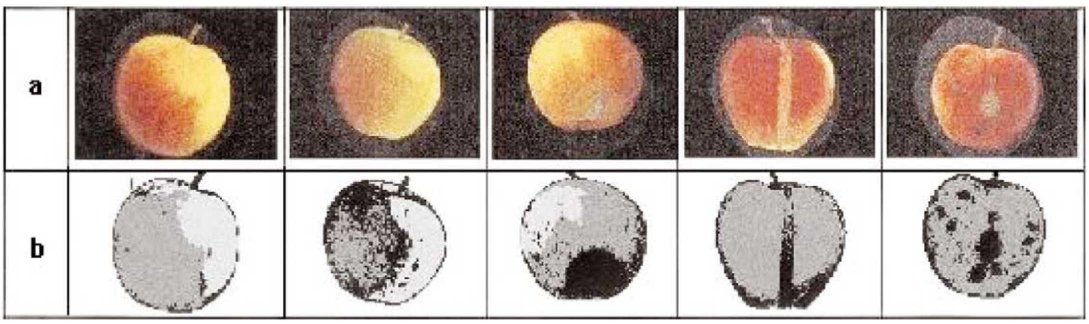

Fig. 4. Results of the algorithms. Row a: original images including healthy fruit with neat transition area, healthy fruit with a chaotic transition area, poorly contrasted defect, well contrasted linear russet, and result of a scab attack; row b: result of the segmentation (Leemans, 1999).

segment apple defects (Leemans *et al.*, 1999). The colour 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 colour. Figure 4 shows five representative original apple images and the results obtained from this method. An important caveat is that classify-based segmentation methods lack a structured way for coping with variations in rotation and scale, which limits their applicability.

Object measurement

Once the image is successfully segmented into discrete objects of interest, the objects can be described and represented for further processing and analysis by measuring the individual features of each object. In general, a segmented object can be represented in features of its external characteristics or internal characteristics. Many features can be used to describe an object, which are compared with the information from known objects to classify an object into one of many categories. Generally, the features that are the simplest to measure and that contribute substantially toward the classification are the best to use. Measurements that can be performed on features in images for food quality evaluation can be grouped into four classes: size, shape, colour, and texture. For each class, a number of different specific measurements can be made, and there are a variety of different ways to perform the operations. Most image analysis systems offer at least a few measures in each class and produce a numeric output suitable for analysis of the processed images.

Size

Three commonly used features for size measurement of an object can be found for food quality evaluation: area, perimeter, and length and width. The most basic convenient measurement for size is the area. For pixel-based representation, this is the number of pixels within the area, which is straightforwardly determined by counting. Cober, Voldeng, and Fregeau-Reid (1997) measured the seed size (cross-sectional area) in two orientations to estimate heritability of seed size in soybean. The perimeter of an object is particularly useful for discriminating between objects with simple and complex shapes. Area and perimeter measurements are easily computed during the extraction of an object from a segmented image. Monnin (1994) designed a system for a multiple-lane cracker baking process. The system used diameter, area, and thickness to measure the crackers. The measured data are displayed on a computer screen for the operator to control dough forming and baking processing. The length and width of an object can also be used to measure the size of an object. It is necessary to locate the major axis of the object and measure its relative length and width. Vandevooren, Polder, and Vanderheijden (1992) statistically analyzed the measurements of length, width, and a range of more or less complex shape descriptors to identify mushroom cultivars. Van Eck, van der Heijden, and Polder (1998) developed an accurate method for measurement of the length, width, and shape of cucumber. To obtain a condensed description, the local width along the midline of cucumber was determined. From this condensed description, length, and width can be extracted. Sapirstein and Kohler (1999) investigated the effect of sampling on the precision and accuracy of digital image analysis of different commercial sample grades of Canada Western Red Spring (CWRS) wheat. Kernel perimeter, length, width, and area measurements were used to determine mean and dispersion statistics of grades of CWRS samples.

Shape

Shape is one of the most common object measurements for food quality evaluation. Compared with other features such as colour and texture, shape is easier to measure using image processing techniques. Frequently, the objects of one class can be distinguished from the

Table 5. Shape features combining with size

$$AreaRatio = \frac{Area}{MaxDiameter \cdot MinDiameter}$$

$$AspectRatio = \frac{MaxDiameter}{MinDiameter}$$

$$Circularity = \frac{Perimeter^2}{Area}$$

$$Compactness = \frac{4\pi \cdot Area}{Perimeter^2}$$

$$DiameterRange = MaxDiameter - MinDiameter$$

$$Eccentricity = \sqrt{1 - \frac{SemiMinor^2}{SemiMajor^2}}$$

$$Roundness = \frac{4\pi \cdot Area}{\pi \cdot MaxDiameter^2}$$

$$ShapeFactor1 = \frac{4\pi \cdot Area}{Perimeter^2}$$

$$ShapeFactor2 = \frac{MaxDiameter}{Area}$$

$$ShapeFactor3 = \frac{Area}{MaxDiameter^3}$$

$$ShapeFactor4 = \frac{4 \cdot Area}{\pi \cdot MaxDiameter\, MinDiameter}$$

others by their shapes, which are physical dimensional measurements that characterise the appearance of an object. Shape features can be measured independently and by combining size measurements.

Combination of size measurements

The earliest class of shape descriptors is simply the combination of size parameters. Table 5 summarizes some of the most widely used shape features with combinations of size measurements for food products. Miller (1992) applied a digital image system to analyse Florida grapefruit for shape classification. In this application, four features, i.e. area ratio, circularity, diameter range and aspect ratio, were used to evaluate acceptable and misshaped Florida grapefruit. The aspect ratio was found to be the most significant one among these four features. To estimate heritability of seed shape in soybean, Cober *et al*. (1997) used two aspect ratios to quantify seed shape. Each aspect ratio was calculated from a different seed orientation with digital image analysis. Shouche, Rastogi, Bhagwat, and Sainis (2001) measured area, perimeter, lengths of major and minor axises, compactness, axis ratio, roundness, shape factor 1, shape factor 2, shape factor 3, and shape factor 4 (defined in Table 5) for shape feature analyses of Indian wheat varieties from the binary images. The area of a region was defined as the number of pixels contained within its boundary. Its perimeter was the length of its boundary. Compactness, axis ratio, roundness, shape factor 1, shape factor 2, shape factor 3, and shape factor 4 were derived from the values of axis length, perimeter and area. For judging the overall shape of tomatoes, compactness and eccentricity were measured, which were estimated from the measured parameters, i.e. area, perimeter, major and minor axises (Jahns, Nielsen, & Paul, 2001). Coppenolle, Paulus, and Schrevens (2002) proposed a methodological concept to study visual preference for length, width and ovality of a traditional fresh, high-quality chicory product using an image system. Shape factor 1 as defined in Table 5 was computed for each of the lentils in the image to ensure that only the size of singulated objects, the nearly circular objects with shape factor 1 >0.9, was measured (Shahin & Symons, 2003).

Independence of size measurements

Various techniques for shape description independent of size measurements were investigated for food quality evaluation. Among those techniques, most applications are based on Fourier descriptor and invariant moments. The Fourier transform of one cycle of the boundary function is an alternative representation of the associated object's shape. Only the low-order Fourier coefficients are required to characterize the basic shape of the object and are candidates for shape descriptors. Invariant moments have some of the properties that good shape feature must have, which are insensitive to translation, rotation and scale changes and can be used to measure shape features.

Fourier descriptor is a plausible technique for shape measurement of food products. Han, Feng, and Weller (1996) developed a corn kernel classification procedure in the frequency domain using a two-dimensional Fourier transform for inspection of stress cracks. A fast Fourier transform algorithm was applied to the preprocessed images, and the transformation results were condensed into 33 feature signatures representing position or orientation invariant morphological features. Paulus and Schrevens (1999) investigated an image processing algorithm based on Fourier expansion to objectively characterize shape of different apple cultivars. Shape characteristics of the periphery of digitised video images were developed. Principal component analysis of the resulting Fourier coefficient showed that two shape variables were required to accurately measure apple profiles, with four images per apple being necessary to adequately describe the shape of an apple. Paliwal, Shashidhar, and Jayas (1999) developed a machine vision algorithm to distinguish the grain kernels. It was found that shape function (Fourier descriptors in polar coordinates) was the most important attribute for grain kernel identification. Fourier descriptors were used to characterize contour of digitised cross-sections of apple fruit and were applied to principal component analysis (Currie *et al*., 2000).

The magnitudes of invariant moments reflect the shape of the object and can be used in food quality evaluation to distinguish among the different objects. Zion, Shklyar, and Karplus (2000) developed an image-processing algorithm to discriminate among the species of St. Peter's fish, grey mullet, and common carp. The algorithm was based on the method of moment-invariants (MI) as the shape features coupled with geometrical considerations. Identification of grey mullet was based on the MI of the whole fish; however, carp and St. Peter's fish was based on the MI of the tails. Standard, central, normalised central and invariant moments were computed using the grey images of Indian wheat for shape analysis (Shouche *et al*., 2001).

Colour

In image analysis for food products, colour is an influential attribute and powerful descriptor that often simplifies object extraction and identification from an image. Colour vision offers a tremendous amount of spatial resolution that can be used to quantify the colour distribution of ingredients. Colour features of an object can be extracted by examining every pixel within the object boundaries. Colour has proven successful for objective measurement of many types of food products with applications ranging from fruit, grain, meat to vegetable.

Colour has shown to be a viable means of measuring fruit. Miller and Delwiche (1989) developed a colour vision system to inspect and grade fresh-market peaches. Diffused lighting and normalised luminance were used to reduce the red, green and blue inputs to two-dimensional chromaticity coordinates. Peach colour was compared with standard peach maturity colours for classification. Leemans *et al.* (1998) used colour machine vision for defect segmentation on Golden Delicious apples. A colour model was used as a standard for comparison with sample images. With two further steps refining the segmentation using either parameters computed on the whole fruit or values computed locally, satisfactory results were achieved. The colour of tomatoes was used for estimating the maturity stage using image analysis (Choi, Lee, Han, & Bunn, 1995; Jahns *et al.*, 2001).

Colour is used extensively for the measurement of grain. Casady, Paulsen, Reid, and Sinclair (1992) developed a trainable algorithm on a colour machine vision system for inspection of soybean seed quality. The variables used for classification were colour chromaticity coordinates and seed sphericity. White and Sellers (1994) developed a high-speed colour inspection system to detect foreign materials on a peanut conveyor belt in real time. The system is trainable to recognise and differentiate unique colour signatures or fingerprints of many types of foreign materials and food products. Ahmad, Reid, Paulsen, and Sinclair (1999) developed a RGB colour feature-based multivariate decision model to discriminate between asymptomatic and symptomatic soybean seeds for inspection and grading, which comprises six colour features including averages, minimums, and variances for RGB pixel values. Overall classification accuracy of 88% was achieved using a linear discriminant function for asymptomatic and symptomatic seeds with highest probability of occurrence. Ruan *et al.* (2001) developed an automatic system to determine weight percentage of scabby wheat kernels, based on colour features of scabby kernels captured by machine vision.

Colour is implemented for the automated inspection and grading of meat products to help to meet the high output and improve objectivity of the industry. The potential of using colour image processing to detect poultry defects such as bruises, skin tears and systemic diseases was investigated (Daley & Thompson, 1992). Park and Chen (1994) used six optical filters at different wavelengths to obtain multispectral images for poultry carcass inspection. Grey level image intensities at selected wavelengths were used to distinguish normal carcasses from 'septicemic' and 'cadaver' carcasses. Lu, Tan, Shatadel, and Gerrard (2000) extracted colour image features from segmented images for evaluating fresh pork. Features including mean and standard deviation of red, green, and blue bands of the segmented muscle area were used in this study. Both statistical and neural network models were employed to predict the colour scores by using the colour image features as inputs. Results of this study showed that an image processing system in conjunction with a neural network was an effective tool for evaluating fresh pork colour.

Colour has also been used in vegetable measurement. Bell peppers were successfully sorted using a colour image analysis system (Shearer & Payne, 1990). RGB pixel intensity values were mapped to one of eight possible hues. The relative hue distributions of pixels in six orthogonal views were calculated and used as colour quantitative variables. Up to 96% accuracy was achieved for grading bell peppers by colour.

Texture

In image analysis, texture is an attribute representing the spatial arrangement of the grey levels of the pixels in a region (Anon., 1990). The texture of a segmented area is an important feature for area description, which quantifies some characteristic of the grey-level variation within the object. Among the texture analysis methods for food quality evaluation, most approaches are statistical including the pixel-value run length method (Li, Tan, Martz, & Heymann, 1999; Majumdar & Jayas, 2000a) and the co-occurrence matrix method (McCauley, Thane, & Whittaker, 1994; Park & Chen, 1996; Shiranita, Miyajima, & Takiyama, 1998). However, several texture description methods are based on Fourier spectrum, wavelet transform, and fractal dimension (Li *et al.*, 2001; Quevedo, Carlos, Aguilera, & Cadoche, 2002; Whittaker, Park, Thane, Miller, & Savell, 1992).

Statistical approaches compute different properties and provide textural characteristics such as smoothness, coarseness, and graininess. They are suitable if texture primitive sizes are comparable with the pixel sizes. McCauley *et al.* (1994) used co-occurrence image texture for both prediction and classification of intramuscular fat in beef from ultrasonic images of both live beef animals and slaughtered carcasses. Park and Chen (1996) demonstrated that it was feasible for discriminating abnormal from normal poultry carcasses at a wavelength of 542 nm with textural feature analysis of multispectral images containing visible/near-infrared wavelengths based on co-occurrence matrices. Shiranita *et al.* (1998) described a method of determining meat quality using the concepts of "marbling score" and texture analysis. The marbling score, being a measurement of the distribution density of fat in the rib-eye region, was considered as a texture pattern. Standard texture feature vectors for each grade were made through using a grey level co-occurrence matrix as a texture feature. The grade of an unevaluated image is determined by comparing the texture feature vector of this unevaluated image with the standard texture feature vectors.

Experimental results show that the system is effective. Li *et al*. (1999) used the beef image texture features to predict cooked-beef tenderness from fresh-beef image characteristics. Two methods, pixel value run length and pixel value spatial dependence, were used to extract muscle image texture features. Statistical and neural network analyses were performed to relate the image features to sensory tenderness scores, and it was found that texture features were useful indicators of beef tenderness. A digital image analysis algorithm was developed to facilitate classification of cereal grains using textural features of individual grains (Majumdar & Jayas, 2000a). The textural features of individual kernels were extracted from different colours and colour band combinations of images. There were 25 textural features used in the discriminant analysis, i.e. 10 grey level co-occurrence matrix features, 12 grey level run length matrix features, and three grey level features.

Another convenient way to determine the texture of an object is to examine its spatial frequency content. To analyze image with texture features, Whittaker *et al*. (1992) used Fourier transform extracted from ultrasonic images for prediction of a beef marbling score. Wavelet textural analysis can be viewed as a combination of spectral and statistical methods. It is based on the wavelet transform and decomposition of an image for different textural orientations, and then the statistic of each decomposed component is computed as one of the textural features of the image. Li *et al*. (2001) used a wavelet-based decomposition method to extract texture features of fresh-beef images, which were used to classify steaks into tough and tender groups in terms of cooked-beef tenderness. Fractal technology can also be used for determining texture feature by analyzing the surface intensity using the fractal dimension, i.e. the fractal texture. Quevedo *et al*. (2002) used fractional Brownian motion, box counting, and fractal dimension (FD) estimation from frequency domain to numerically describe the surfaces of foods and the microstructure of potato cells for texture analysis. Using the power-law scaling for self-similar fractals, a FD was calculated for each image. The surface of analysed foods had FD of 2.22 for chocolate and 2.44 for pumpkin shell.

In addition to size, shape, colour, and texture, moisture content also plays a crucial role in prediction of the deterioration of food quality. MRI has been extensively used in the past to measure non-invasively the moisture content within different components of food products with good spatial resolution. The data obtained with MRI has been used for modelling transient moisture profiles of a drying apple slab (McCarthy & Perez, 1991), studying the rehydration of extruded pasta (Hills, Babonneau, Quantin, Gaudet, & Belton, 1996), characterizing osmotic dehydrated apple (Cornillon, 2000), real time measuring the moisture profile change of rice grain (Takeuchi, Fukuoka, Gomi, Maeda, & Watanabe, 1997), measuring moisture distribution of wheat (Song, Delwiche, & Line, 1998), observing moisture migration of confection (Troutman, Mastikhin, Balcom, Gads, & Zregler, 2001), and acquiring water mobility and moisture data of strawberry (Evans, Brambilla, Lane, Torreggiani, & Hall, 2002). Recently, electromagnetic imaging, a relatively new imaging technique, has been applied to non-destructively measure moisture. Abdullah, Aziz, and Mohamed (2000) employed electromagnetic imaging for mapping the moisture content in grain. The method is shown to be quite efficient in mapping grain anomalies in the moisture range of 12–39%.

Classification

Classification identifies objects by classifying them into one of the finite sets of classes, which involves comparing the measured features of a new object with those of a known object or other known criteria and determining whether the new object belongs to a particular category of objects. A wide variety of approaches have been taken towards this task in the food quality evaluation. Statistical, fuzzy logic, and neural network are three main methods of classification in the literature. They have a common objective which is to simulate a human decision-maker's behaviour, and have the advantage of consistency and, to a variable extent, explicitness.

Statistical classification

Statistical approaches are generally characterized by having an explicit underlying probability model, which provides the probability of being in each class rather than a simple classification. Several statistical classification methods have been developed to sort food products such as poultry carcasses, apples, cereal grains, and muffins.

A statistical classifier based on multispectral image co-occurrence matrix analysis was developed for poultry carcasses inspection (Park & Chen, 1996). The classification was perfect when the normal carcasses were separated from the abnormal, i.e. septicemic and cadaver carcasses. However, for separating condemned carcasses between septicemic and cadaver, the accuracy was 96% for septicemic and 82.7% for cadaver cases. Tao, Shao, Skoeles, and Chen (2000) explored the possibility of detecting splenomegaly with a computer imaging system. Statistical classification was developed to detect abnormalities. Based on a total of 57 turkey sample images, correct classification rates of 92 and 95% in detection of spleen abnormality were obtained using a self test set and an independent test set, respectively. For sorting red delicious apples, a linear Bayesian classifier with three input features, i.e. fruit area in the segmented image, mean intensity of fruit in the original image, and 10th harmonic of the discrete cosine transform, was used and an accuracy of 79% achieved (Shahin, Tollner, Evans, & Arabnia, 1999). Furthermore, a k-nearest neighbour statistical classifier was applied for classification of cereal grains using a selected set of 15 morphological and 13 colour features extracted from the grain sample images (Luo, Jayas, & Symons, 1999). The classifier was trained and tested with three different training and testing data sets and the average classification accuracies were 98.2, 96.9, 99.0, 98.2, and 99.0% for Canadian Western Red Spring (CWRS) wheat, Canadian Western Amber Durum (CWAD) wheat, barley, rye, and oats, respectively. Abdullah *et al*. (2000) developed an automated system for visual inspection of muffins incorporating multivariate discriminant algorithms to statistically classify muffins based on surface colour. The classification algorithm separated dark from light coloured muffins and the precision of colour classification was evaluated using pregraded and ungraded muffins. The automated system was able to correctly classify 96% of pregraded and 79% of ungraded muffins.

Fuzzy classification

Compared with traditional classification techniques, fuzzy classification groups individual samples into classes that do not have sharply defined boundaries. The characteristic benefit of fuzzy classification is that the degree of membership functions can provide more information about the confidence of the class assignment. Recently, fuzzy classification methods have been used for grading fish products, rating tomatoes, and classifying pizza.

Hu, Gosine, Cao, and de Silva (1998) presented an application of a fuzzy classification technique for automated grading of fish products. A fuzzy classifier with a four-level hierarchy was developed based on the 'generalised K-nearest neighbour rules'. Both conventional and fuzzy classifiers were examined using a realistic set of herring roe data to compare the classification performance in terms of accuracy and computational cost. The classification results show that the generalised fuzzy classifier provides the best accuracy of 89%. To achieve an automatic grading of tomato, Jahns *et al*. (2001) proposed a tomato quality rating method based on a fuzzy model. Starting with visual appearance quality attributes such as size, colour, shape, defects and abnormalities obtained by image analysis, a fuzzy method is proposed for mapping various fuzzy consumer aspects to overall quality classes. The objective of such a mapping is to achieve an automatic rating of fruit quality, modelling consumer aspects and producer needs. Sun and Brosnan (2003a, 2003b) developed a fuzzy logic system to classify the sauce spread samples and the pizza topping quality into classes of acceptable and defective quality. The experimental results for the sauce spread analysis and the pizza topping quality show that by using computer vision in conjunction with fuzzy logic a classification accuracy of 92% and an accuracy of 100% were achieved, respectively.

Neural network classification

Neural network approaches combine the complexity of some of the statistical techniques with the machine learning objective of imitating human intelligence. The complete network represents a very complex set of interdependencies that may incorporate any degree of nonlinearity. For food product classification, very general functions can be modelled to transform physical properties into quality factors. The artificial neural networks have applicability to a number of types of food product classification including grains, fruits, poultry carcass, and vegetable.

Neural network has been used to grade cereal grains. Five different kinds of cereal grains, i.e. Hard Red Spring (HRS) wheat, Canada Western Amber Durum (CWAD) wheat, barley, oats, and rye, were used to evaluate the classification accuracy of nine different neural network architectures (Paliwal, Visen, & Jayas, 2001). Eight morphological features, i.e. area, perimeter, length of major axis, length of minor axis, elongation, roundness, Feret diameter, and compactness were extracted and used as input to the neural networks for each kernel. The classification accuracies were in excess of 97% for HRS wheat, CWAD wheat and oats, while about 88% for barley and rye. A multilayer neural network classifier was applied for the classification of cereal grains and for the classification of healthy and six types of damaged Canadian Western Red Spring wheat kernels, using selected morphological and colour features extracted from the grain sample images (Luo *et al*., 1999).

It is feasible for neural network to classify fruits like apples and pistachio nuts. Nakano, Kurata, and Kaneko (1992) developed a method that can classify the quality of the external appearance of apples using a neural network. The model was three layers neural network with 27 units in the input layer, 10 units in the hidden layer, and three units in the output layer. The experimental results proved that the classifier had the ability to classify quality into three grades of external appearance of apples. Nakano (1997) applied two neural network models to the colour grading of apples. One is used to classify pixels and the accuracy is more than 95%. Another neural network was developed that can grade the whole surface colour of an apple into 'superior', 'excellent', 'good', 'poor colour', and 'injuried'. The grade accuracies for 'superior', 'poor colour', and 'injuried' were very high, but the accuracies for 'excellent' and 'good' were not very high. A neural network classifier was used to categorise apples into three different watercore levels, i.e. clean, mild, and severe, using eight features extracted from an X-ray scanned apple image (Kim & Schatzki, 2000). The results showed that the system was able to correctly recognise apples into clean and severe categories with error within ±5–8%. Kavdir and Guyer (2002) sorted Empire and Golden Delicious apples based on their surface quality conditions using backpropagation neural networks. A 2-class and a 5-class classification were performed with pixel grey values and texture features obtained from the entire apple image as its input. Classification success in the 2-class classification rated from 89.2 to 100%. In the 5-class classification, classification success rates for Empire apples were between 93.8 and 100%, while classification success rates for Golden Delicious apples were between 89.7 and 94.9%. Ghazanfari, Irudayaraj, and Kusalik (1996) proposed a multi-structure neural network (MSNN) classifier which consisted of four parallel discriminators to classify four classes of pistachio nuts. Each discriminator was a feed-forward neural network with two hidden layers and a single-neuron output layer using physical attributes of the nuts extracted from their images as input. 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. Casasent, Sipe, Schatzki, Keagy, and Lee (1998) used a new neural network for classification of X-ray pistachio nut image. With fewer hidden layer neurons than other classifiers, this neural network produced higher-order decision surfaces. It used new techniques to select the number of hidden layer neurons and adaptive algorithms that avoid ad hoc parameter selection problems, which allows selection of the best classifier parameters without the need to analyse the test set results. The classification results indicated the potential to reduce major defects to 2% with only 1% of good nuts rejected.

Neural network has also been used to classify poultry carcass. Park, Chen, Nguyen, and Hwang (1996) developed a multispectral imaging system for carcass inspection. 91.4% accuracy was achieved for the separation of tumorous carcasses from normals based on the spectral images scanned at both 542 and 700 nm wavelengths by a neural network classifier. For on-line poultry carcass inspection, Park and Chen (2000) examined neural network models with different learning rules (delta and hyperbolic tangent) and transfer functions (sigmoid and norm-cum-sigmoid) using features extracted from spectral images. The optimum neural classifier utilised a delta learning rule and a hyperbolic tangent transfer function. Classification accuracy was 91.1% for wholesome and 83.3% for unwholesome carcasses when the spectral images at 540 nm, 700 nm and their ratio were used as inputs to the neural network model.

Several kinds of vegetable such as carrots and onions are graded by neural network methods. Brandon, Howarth, Searcy, and Kehtarnavaz (1990) designed a neural network to classify carrot tips into five classes using shape features. Trained with 80 simulated carrot tips and tested with 250 fresh market carrots, the average misclassification rate was 11.5%. Shahin, Tollner, Gitaitis, Summer, and Maw (2002) reported that spatial edge features combined with selected discrete cosine transform coefficients proved to be good indicators for internal defects using X-ray imaging of sweet onions. A neural classifier performed better than the Bayesian classifier for sorting onions into two classes (good or defective) by achieving an overall accuracy of 90%.

Discussion

The image acquisition problem is ill-posed because conflicting criteria need to be fulfilled: cost versus accuracy. CCD camera is the cheapest way for image acquisition, but not suitable for internal capturing structures. Ultrasound, MRI, CT, and ET can be applied to inspect internal features, but more expensive. Furthermore, ultrasound and ET cost less than MRI and CT. Although MRI and CT offer advantages in image resolution and accuracy, Cross and Belk (1994) took use of A-mode, B-mode and real-time ultrasound techniques for objective measurements of meat quality. The ultrasound measurement was also incorporated into national genetic programs for lamb carcass quality improvement (Davis & Fennessy, 1996). The high cost of the more accurate methods, such as CT and MRI, limits access for evaluation of food internal quality. Being low costs, the ultrasound and ET technique will be the method of choice for food internal quality evaluation in the future, despite its relatively low precision. However, in some cases, the precision of the ultrasound technique is not sufficient, which narrows the range of its use. ET is structural dependence and suffers from poor resolution. Compared to ultrasound and ET, CT would double the rate of genetic improvement for lean meat traits in lambs as direct selection was possible for protein content and proportions of lean, intermuscular and intramuscular fat (Jopson, Kolstad, Sehested, & Vangen, 1995). MRI can obtain similar accuracy as CT for food internal quality evaluation. For example, MRI and CT have similar accuracy for measuring adipose tissue distribution (Seidell, Bakker, & van der Kooy, 1990). However, using spectroscopy, MRI can provide more information than CT. The accuracy of MRI at predicting body composition is higher than that of CT (Simm, 1992).

In order to ensure the performance of an image processing system, image pre-processing is necessary to enhance the region that we are concerned with and remove the noises. The ROI (regions of interest) can be improved by different transformations of RGB colour space (discriminant analysis, canonical transformation, i1i2i3, HSI, HSV and $L^*a^*b^*$) by weighting each channel in a different way (Philipp & Rath, 2002). Noises are equivalent to the high frequencies in the Fourier transform domain, which can be suppressed by lowpass filter. Meanwhile, it will blur the image and decrease the resolution, which will impact the subsequent image processing. Therefore, finding the best transformation method for the pre-processing of food product image is an interesting issue for further research.

Segmentation of food image is very important for food quality evaluation since its performance directly affects the result of the subsequent image processing steps. If objects in image cannot be segmented correctly, it is difficult for object measurement and classification, and hence will impact evaluating the food product image. There are four common image segmentation methods available, i.e. thresholding-based, region-based, gradient-based, and classification-based segmentation, however, no general algorithms will work for all images. Almost all image segmentation techniques proposed so far are ad hoc in nature (Fu & Mui, 1981). The central problem encountered in image segmentation is how to choose a suitable approach to partition the image into homogeneous regions when there are many possible ways of doing it. The possible solution is to select a segmentation method based on prior knowledge about the image content. The prior knowledge available can be the special size, shape, colour, and texture of objects and the spatial distribution information of objects.

A single group of features such as size, shape, colour, and texture alone is inadequate for quality evaluation of many food products. Tan, Gao, and Hsieh (1992) extracted colour and texture features of an extruded food product to determine changes in the product appearance as a result of changes in the extrusion process. A high-speed image processing system called ROBSORTER was used to sort pieces of diced and sliced confectionery ginger by size and shape into up to five grades, at a speed of up to 45 pieces per second (Kassler, 1994). Davidson, Ryks, and Chu (2001) used physical features of chocolate chip cookies such as size, shape, baked dough colour and fraction of top surface area for image analysis. A fundamental problem within the field of object measurement is which image features are the best to correlate with the product quality. Object measurement should attempt to find those descriptive parameters, usually numeric, which succinctly represent the information of importance in the image. Majumdar and Jayas (2000b) developed classification models by combining two or three feature sets, i.e. morphological, colour, and textural, to classify individual kernels of cereal grains. The mean accuracies were 98.6 and 99.3% using the morphology-texture model, 99.4 and 99.6% using the morphology-colour model, and 98.4 and 98.0% using the texture-colour model with the 15 most significant features for the independent and the training data sets, respectively. The highest classification accuracies of 99.7 and 99.8% were achieved when the morphology–texture–colour model was used for the independent and the training data sets, respectively. An overview of features used for food product quality evaluation is given in Table 6, which shows that shape and colour are the most frequently applied features.

Table 6. Different classes of features applied to various food products

Category	Products	Size	Shape	Colour	Texture
Fishery	Carp		√		
	Mullet		√		
	Oyster	√	√		
Fruit	Apple		√	√	
	Grapefruit		√		
	Peach			√	
	Tomato	√	√	√	
Grain	Barley				√
	Peanut			√	
	Rye				√
	Soybean	√	√	√	
	Wheat	√	√	√	√
Meat	Beef	√	√	√	√
	Chicken			√	
	Pork			√	√
	Poultry carcass			√	√
Vegetable	Carrot		√		
	Chicory		√		
	Lentil		√		
	Mushroom	√		√	
	Pepper			√	
	Potato	√	√	√	√
Others	Biscuit	√	√		
	Cookies	√	√	√	
	Muffin		√	√	
	Pizza		√	√	

One problem existing in the classification is the issue of computational complexity. The computationally hard part of classification is inducing a classifier, which takes a set of features that characterize objects and uses them to determine the class of each object. The classification problem becomes very hard when there are many features caused by the inability of existing classifier to cope adequately with a large number of parameters. The other problem is the issue of classification accuracy and which classifier should be used for optimal classification. Classifier can give simple yes or no answers or an estimate of the probability that an object belongs to each of the candidate classes. Luo *et al.* (1999) applied two statistical and one neural network classifiers empirically compared for the classification of healthy and six types of damaged Canadian Western Red Spring wheat kernels using selected morphological and colour features extracted from the grain sample images.

Table 7. Summary of classification methods for food quality evaluation

Category	Products	Methods	Accuracy (%)	References
Fishery	Fish	Fuzzy	89	Hu *et al.* (1998)
Fruit	Apple	Statistical	79	Shahin *et al.* (1999)
		Neural network	92	Kim and Schatzki (2000)
	Pistachio nuts	Neural network	95.9	Ghazanfari *et al.* (1996)
Grain	Barley	Statistical	99.0	Luo *et al.* (1999)
		Neural network	88	Paliwal *et al.* (2001)
	Rye	Statistical	98.2	Luo *et al.* (1999)
		Neural network	88	Paliwal *et al.* (2001)
	Oat	Statistical	99.0	Luo *et al.* (1999)
		Neural network	97	Paliwal *et al.* (2001)
	Wheat	Statistical	96.9	Luo *et al.* (1999)
		Neural network	97	Paliwal *et al.* (2001)
Meat	Poultry carcasses	Statistical	92	Tao *et al.* (2000)
		Neural network	91.1	Park and Chen (2000)
Vegetable	Carrot	Neural network	88.5	Brandon *et al.* (1990)
	Tomato	Fuzzy	—	Jahns *et al.* (2001)
	Onion	Neural network	90	Shahin *et al.* (2002)
Others	Muffin	Statistical	79	Abdullah *et al.* (2004)
	Pizza	Fuzzy	92	Sun and Brosnan (2003a, 2003b)

They found that the k-nearest neighbour statistical classifier and the multilayer neural network (MNN) classifier gave similar classification results, while the classification accuracies achieved using a parametric classifier were lower than those achieved using both the k-nearest neighbour and the MNN classifiers. Table 7 lists the comparable results of different classification methods used for different food product quality evaluation.

Conclusions

According to the five steps in the image processing chain, the applications of image processing techniques to the different types of food product are reviewed in this paper. A variety of image processing techniques are used to perform the food quality evaluation with various degrees of success:

- CCD, MRI, Ultrasound, CT and ET are the most popular sensor techniques used in image acquisition for food quality evaluation. While CCD camera is usually used to capture external attributes, MRI, Ultrasound, CT, and ET can be used to inspect internal structure.
- Two image pre-processing methods, i.e. pixel and local pre-processing, can be utilised to improve the quality of an image for further processing. Colour space transformation is the most popular approach for pixel pre-processing, and image smoothing techniques are significant for local pre-processing.
- Thresholding-based, gradient-based, region-based, and classification-based approaches are the four main techniques applied to segment food products. Thresholding-based approach segments image by partitioning the image into sets of interior and exterior points, however, gradient-based approaches are based on the detection of the edges of the object, while classification-based methods are achieved by assigning each pixel to different objects. Furthermore, GM and SM are the two basic principles for region-based approaches.
- Size, shape, colour, and texture are the four most common classes used to measure the object features in the food product image. Area, perimeter, length and width are the ordinary features used to reflect the size of an object. Shape features can be used independently of, or in combination with, size measurements. Fourier descriptor and invariant moments are the two categories independent of size measurements used for shape description. Statistical is the major texture description method and several other texture description methods are based on Fourier spectrum, wavelet transform, and fractal.
- Three main methods, i.e. statistical, fuzzy logic, and neural network, are currently employed to perform classification. Statistical approaches are generally characterized by having an explicit underlying probability model, fuzzy classification uses the fuzzy logic concepts, and neural network simulate biological nervous systems.

The major barrier for image techniques applying to the food quality evaluation is the budget constraints. An image processing system is still nonviable in many potential applications for the unacceptable cost. To satisfy the demand for cost-effective, developing cheap multipurpose image processing systems is especially important to the food quality evaluation. Processing speed is still a bottle-neck in heavy-duty real-time applications, failing to handle the large data streams. On one hand, developing adequately efficient and accurate image processing algorithms can accelerate processing speed to meet modern manufacturing requirements. On the other hand, integrating image processing algorithms onto specialised hardware can significantly reduce the consuming of time. With cheap and fast solutions in software and hardware, image processing techniques will play more and more important role in the food quality evaluation.

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