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Review

Improving quality inspection of food products by computer vision—a review

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Abstract

With increased expectations for food products of high quality and safety standards, the need for accurate, fast and objective quality determination of these characteristics in food products continues to grow. Computer vision provides one alternative for an automated, non-destructive and cost-effective technique to accomplish these requirements. This inspection approach based on image analysis and processing has found a variety of different applications in the food industry. Considerable research has highlighted its potential for the inspection and grading of fruits and vegetables. Computer vision has been successfully adopted for the quality analysis of meat and fish, pizza, cheese, and bread. Likewise grain quality and characteristics have been examined by this technique. This paper presents the significant elements of a computer vision system and emphasises the important aspects of the image processing technique coupled with a review of the most recent developments throughout the food industry.
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Keywords: Machine vision; Computer vision; Image processing; Image analysis; Fruit; Vegetables; Grain; Meats; Online inspection

Contents

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1. Introduction

The increased awareness and sophistication of consumers have created the expectation for improved quality in consumer food products. This in turn has increased the need for enhanced quality monitoring. Quality itself is defined as the sum of all those attributes which can lead to the production of products acceptable to the consumer when they are combined. Quality has been the subject of a large number of studies (Shewfelt & Bruckner, 2000). The basis of quality assessment is often subjective with attributes such as appearance, smell, texture, and flavour, frequently examined by human inspectors. Consequently Francis (1980) found that human perception could be easily fooled. Together with the high labour costs, inconsistency and variability associated with human inspection accentuates the need for objective measurements systems. Recently automatic inspection systems, mainly based on camera—computer technology have been investigated for the sensory analysis of agricultural and food products. This system known as computer vision has proven to be successful for objective measurement of various agricultural (He, Yang, Xue, & Geng, 1998; Li & Wang, 1999) and food products (Sun, 2000; Wang & Sun, 2001).

Computer vision includes the capturing, processing and analysing images, facilitating the objective and non-destructive assessment of visual quality characteristics in food products (Timmermans, 1998). The potential of computer vision in the food industry has long been recognised (Tillett, 1990) and the food industry is now ranked among the top 10 industries using this technology (Gunasekaran, 1996). Recent advances in hardware and software have aided in this expansion by providing low cost powerful solutions, leading to more studies on the development of computer vision systems in the food industry (Locht, Thomsen, & Mikkelsen, 1997; Sun, 2000). As a result automated visual inspection is under going substantial growth in the food industry because of its cost effectiveness, consistency, superior speed and accuracy. Traditional visual quality inspection performed by human inspectors has the potential to be replaced by computer vision systems for many tasks. There is increasing evidence that machine vision is being adopted at commercial level (Locht et al., 1997). This paper presents the latest developments and recent advances of computer vision in the food industry. The fundamental elements of the systems and technologies involved are also examined.

2. Fundamentals of computer vision

Following its origin in the 1960s, computer vision has experienced growth with its applications expanding in diverse fields: medical diagnostic imaging; factory automation; remote sensing; forensics; autonomous vehicle and robot guidance.

Computer vision is the construction of explicit and meaningful descriptions of physical objects from images (Ballard & Brown, 1982). The term which is synonymous with machine vision embodies several processes. Images are acquired with a physical image sensor and dedicated computing hardware and software are used to analyse the images with the objective of performing a predefined visual task. Machine vision is also recognised as the integrated use of devices for non-contact optical sensing and computing and decision processes to receive and interpret an image of a real scene automatically. The technology aims to duplicate the effect of human vision by electronically perceiving and understanding an image (Sonka, Hlavac, & Boyle, 1999). Table 1 illustrates the benefits and drawbacks associated with this technology.

2.1. Hardware

A computer vision system generally consists of five basic components: illumination, a camera, an image

Table 1
Benefits and drawbacks of machine vision

	Reference
Advantages	
Generation of precise descriptive data	Sapirstein (1995)
Quick and objective	Li, Tan, and Martz (1997)
Reducing tedious human involvement	
Consistent, efficient and cost effective	Lu, Tan, Shatadal, and Gerrard (2000)
Automating many labour intensive process	Gunasekaran (2001)
Easy and quick, consistent	Gerrard, Gao, and Tan (1996)
Non-destructive and undisturbing	Tao, Heinemann, Varghese, Morrow, and Sommer (1995a), Zayas, Martin, Steele, and Katsevich (1996)
Robust and competitively priced sensing technique	Gunasekaran and Ding (1993)
Permanent record, allowing further analysis later	Tarbell and Reid (1991)
Disadvantages	
Object identification being considerably more difficult in unstructured scenes	Shearer and Holmes (1990)
Artificial lighting needed for dim or dark conditions	Stone and Kranzler (1992)

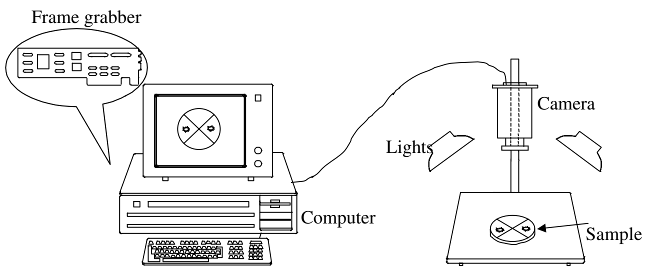

Fig. 1. Components of a computer vision system (Wang & Sun, 2002a).

capture board (frame grabber or digitiser), computer hardware and software as shown in Fig. 1 (Wang & Sun, 2002a).

As with the human eye, vision systems are affected by the level and quality of illumination. Sarkar (1991) found that by adjustment of the lighting, the appearance of an object can be radically changed with the feature of interest clarified or blurred. Therefore the performance of the illumination system can greatly influence the quality of image and plays an important role in the overall efficiency and accuracy of the system (Novini, 1995). In agreement Gunasekaran (1996) noted that a well-designed illumination system can help to improve the success of the image analysis by enhancing image contrast. Good lighting can reduce reflection, shadow and some noise giving decreased processing time. Various aspects of illumination including location, lamp type and colour quality, need to be considered when designing an illumination system for applications in the food industry (Bachelor, 1985). Gunasekaran (2001) found that most lighting arrangements can be grouped as either front or back lighting. Front lighting (electron projection lithography or reflective illumination) is used in situations where surface feature extraction is required such as defect detection in apples (Yang, 1994). In contrast back lighting (transmitted illumination) is employed for the production of a silhouette image for critical edge dimensioning or for sub-surface feature analysis as in the size inspection of chicken pieces (Soborski, 1995). Light sources also differ but may include incandescent, fluorescent, lasers, X-ray tubes and infrared lamps. The choice of lamp affects quality and image analysis performance (Bachelor, 1985). The elimination of natural light effects from the image collection process is considered of importance with most modern systems having built in compensatory circuitry.

There are many different sensors which can be used to generate an image, such as ultrasound, X-ray and near infrared spectroscopy. Images can be also obtained using displacement devices and documents scanners. Typically the image sensors used in machine vision are usually based on solid state charged coupled device (CCD) camera technology with some applications using thermionic tube devices. CCD cameras are either of the array type or line scan type. Array or area type cameras consist of a matrix of minute photosensitive elements (photosites) from which the complete image of the object is obtained based on output proportional to the amount of incident light. Alternatively line scan cameras use a single line of photosites which are repeatedly scanned up to 2000 times per minute to provide an accurate image of the object as it moves under the sensor (Wallin & Haycock, 1998). Monochrome and colour cameras have been used throughout the food industry for a variety of applications (Leemans, Magein, & Destain, 1998; Pearson & Slaughter, 1996; Steinmetz, Roger, Molto, & Blasco, 1999; Yang, 1996). X-ray radiography has also been used for the generation of images for computer vision analysis of a variety products such as water core in apples (Kim & Schatzki, 2000) and for the detection of bones in chicken and fish (Jamieson, 2002). Table 2 shows the different applications using X-ray imaging in computer vision.

Table 2
Applications using X-ray imaging in machine vision

Application	Accuracy (%)	Reference
Detection of bones in fish and chicken	99	Jamieson (2002)
Internal defects of sweet onions	90	Tollner, Shahin, Maw, Gitaitis, and Summer (1999)
Spit pits in peaches	98	Han, Bowers, and Dodd (1992)
Water core damage in apples	92	Kim and Schatzki (2000)
	–	Schatzki et al. (1997)
Pinhole damage in almonds	81	Kim and Schatzki (2001)

The process of converting pictorial images into numerical form is called digitisation. In this process, an image is divided into a two dimensional grid of small regions containing picture elements defined as pixels by using a vision processor board called a digitiser or frame grabber. There are numerous types of analogue to digital converters (ADC) but for real time analyses a special type is required, this is known as a 'flash' ADC. Such 'flash' devices require only nanoseconds to produce a result with 50–200 megasamples processed per second (Davies, 1997). Selection of the frame grabber is based on the camera output, spatial and grey level resolutions required, and the processing capability of the processor board itself (Gunasekaran & Ding, 1994).

2.2. Image processing and analysis

Image processing and image analysis are recognised as being the core of computer vision (Krutz, Gibson, Cassens, & Zhang, 2000). Image processing involves a series of image operations that enhance the quality of an

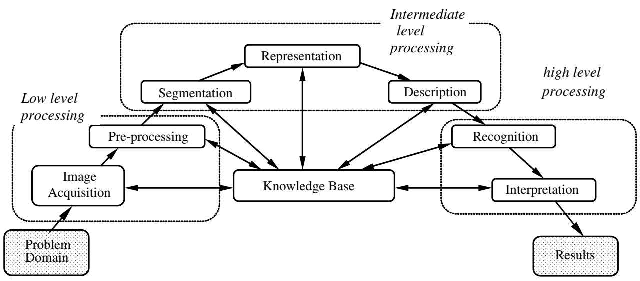

Fig. 2. Different levels in the image processing process (Sun, 2000).

image in order to remove defects such as geometric distortion, improper focus, repetitive noise, non-uniform lighting and camera motion. Image analysis is the process of distinguishing the objects (regions of interest) from the background and producing quantitative information, which is used in the subsequent control systems for decision making. Image processing/analysis involves a series of steps, which can be broadly divided into three levels: low level processing, intermediate level processing and high level processing (Gunasekaran & Ding, 1994; Sun, 2000), as indicated in Fig. 2 (Sun, 2000).

Low level processing includes image acquisition and pre-processing. Image acquisition is the transfer of the electronic signal from the sensing device into a numeric form. Image pre-processing refers to the initial processing of the raw image data for correction of geometric distortions, removal of noise, grey level correction and correction for blurring (Shirai, 1987). Pre-processing aims to improve image quality by suppressing undesired distortions or by the enhancement of important features of interest. 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 edges. Also through the use of different filters fitted to CCD cameras images from particular spectral regions can be collected. Rigney, Brusewitz, and Kranzler (1992) used a 400–620 nm interference filter to examine contrast between defect and good asparagus tissue. A multi-spectral camera system with six band pass filters for the inspection of poultry carcasses was used to achieve better classification of abnormal carcasses (Park & Chen, 1994).

Intermediate level processing involves image segmentation, and image representation and description. Image segmentation is one of the most important steps in the entire image processing technique, as subsequent extracted data are highly dependent on the accuracy of this operation. Its main aim is to divide an image into regions that have a strong correlation with objects or areas of interest. Segmentation can be achieved by three different techniques: thresholding, edge-based segmentation and region-based segmentation as shown in Fig. 3 (Sonka et al., 1999; Sun, 2000). Thresholding is a simple

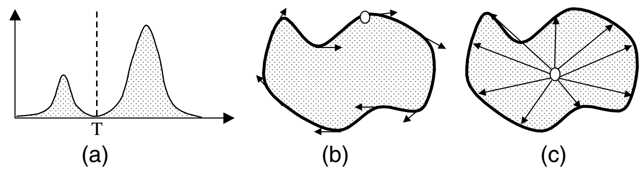

Fig. 3. Typical segmentation techniques: (a) thresholding, (b) edge-based segmentation and (c) region-based segmentation (Sun, 2000).

and fast technique for characterising image regions based on constant reflectivity or light absorption of their surfaces. Edge-based segmentation relies on edge detection by edge operators. Edge operators detect discontinuities in grey level, colour, texture, etc. Region segmentation involves the grouping together of similar pixels to form regions representing single objects within the image. The criteria for like-pixels can be based on grey level, colour and texture. The segmented image may then be represented as a boundary or a region. Boundary representation is suitable for analysis of size and shape features while region representation is used in the evaluation of image texture and defects. Image description (measurement) deals with the extraction of quantitative information from the previously segmented image regions. Various algorithms are used for this process with morphological, textural, and photometric features quantified so that subsequent object recognition and classifications may be performed.

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.

The 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, Jing, Tao, & Zhang, 2003).

3. Applications

Computer vision systems are being used increasingly in the food industry for quality assurance purposes. The system offers the potential to automate manual grading practices thus standardising techniques and eliminating tedious human inspection tasks. Computer vision has proven successful for the objective, online measurement of several food products with applications ranging from routine inspection to the complex vision guided robotic control (Gunasekaran, 1996).

3.1. Bakery products

The appearance of baked products is an important quality attribute, correlating with product flavour and influencing the visual perceptions of consumers and hence potential purchases of the product. Features such as the internal and external appearance contribute to the overall impression of the products quality. Consequently such characteristics have been evaluated by computer vision. Scott (1994) described a system which measures the defects in baked loaves of bread, by analysing its height and slope of the top. The internal structure (crumb grain) of bread and cake was also examined by machine vision (Sapirstein, 1995). The brightness, cell density, cell area and uniformity of the grain analysed indicated that even the most minor deviations from the required specifications were obvious to the developed system, allowing corrective measures in the bakery to be taken sooner. In a more recent study, digital images of chocolate chip cookies were used to estimate physical features such as size, shape, baked dough colour and fraction of top surface area that was chocolate chip (Davidson, Ryks, & Chu, 2001). Four fuzzy models were then developed to predict consumer ratings based on three of the features examined. Automated visual inspection of muffins has also been performed by use of a system developed by Abdullah, Aziz, and Dos-Mohamed (2000). Colour of 200 muffins were examined using the vision system with a classification algorithm used for separating dark from light samples using pregraded and ungraded muffins. Correct classification of 96% of pregraded and 79% of ungraded muffins was achieved when compared with visual inspection.

3.2. Meat and fish

Visual inspection is used extensively for the quality assessment of meat products applied to processes from the initial grading through to consumer purchases. McDonald and Chen (1990) investigated the possibility of using image-based beef grading in some of the earliest studies in this area. They discriminated between fat and lean in longissimus dorsi muscle based on reflectance characteristics, however poor results were reported. Recently greater accuracy was found in a study by Gerrard et al. (1996) where R^2 (correlation coefficient) values of 0.86 and 0.84 for predicted lean colour and marbling were recorded, respectively, for 60 steaks using image analysis. Li et al. (1997) measured image texture as a means of predicting beef tenderness. Colour, marbling and textural features were extracted from beef images and analysed using statistical regression and neural networks. Their findings indicated that textural features were a good indicator of tenderness. Image analysis was also used for the classification of muscle type, breed and age of bovine meat (Basset, Buquet, Abouelkaram, Delachartre, & Culioli, 2000). The meat slices analysed came from 26 animals with the focus of the analysis based on the connective tissue (directly related to meat tenderness) which contains fat and collagen variables with muscle type, breed, age, and clearly is visible on photographic images. The study led to a representation of each meat sample with a 58 features vector and indicated the potential of image analysis for meat sample recognition.

Machine vision has also been used in the analysis of pork loin chop images (Lu et al., 2000; Tan, Morgan, Ludas, Forrest, & Gerrard, 2000). Colour image features were extracted from segmented images (Lu et al., 2000). Both statistical and neural network models were employed to predict colour scores by using the image features as inputs and then compared to the sensory scores of a trained panel. The neural network model was determined as the most accurate with 93% of the 44 samples examined producing a prediction error of less than 0.6. Fig. 4 shows an original and segmented pork loin chop image used in this study. In a similar study over 200 pork lion chops were evaluated using colour machine vision (CMV) (Tan et al., 2000). Agreement between the vision system and the panellists was as high as 90%. The online performance of CMV was also determined in this study with repeatedly classifying 37 samples at a speed of 1 sample per second.

A technique for the spectral image characterisation of poultry carcasses for separating tumourous, bruised and skin torn carcasses from normal carcasses was investigated by Park, Chen, Nguyen, and Hwang (1996). Carcasses were scanned by an intensified multi-spectral camera with various wavelength filters (542–847 nm) with the results indicating that the optical wavelengths of 542 and 700 nm were the most useful for the desired classification. For separating tumourous carcasses from normal ones, the neural network performed with 91% accuracy. Co-occurrence matrix texture features of multi-spectral images were used to identify unwholesome poultry carcasses (Park & Chen, 2001). Both quadratic and linear discriminant models had an accuracy of 97% and 95%, respectively. Defects were also detected using the chromatic content of chicken images (Barni, Cappellini, & Mecocci, 1997). Possible defect areas were first extracted by means of morphological image reconstruction and then classified according to a predefined list of defects. Soborski (1995) investigated the online inspection of shape and size of chicken pieces. Fig. 5 shows a schematic of the system used.

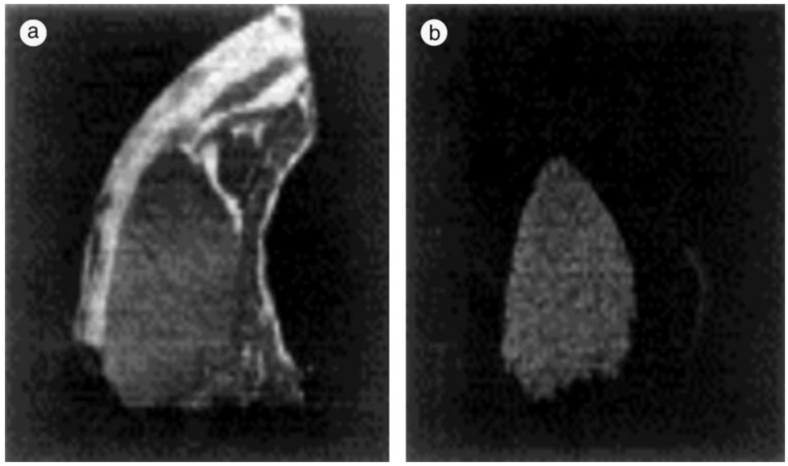

Fig. 4. Pork loin images: (a) original image and (b) segmented muscle image (Lu et al., 2000).

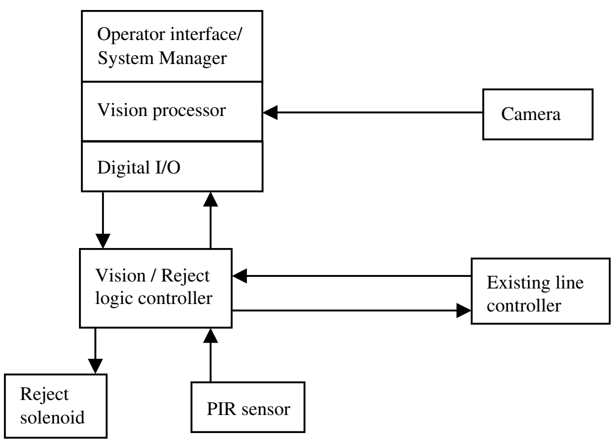

Fig. 5. Flow diagram of a machine vision system for shape/size inspection of chicken pieces (Soborski, 1995).

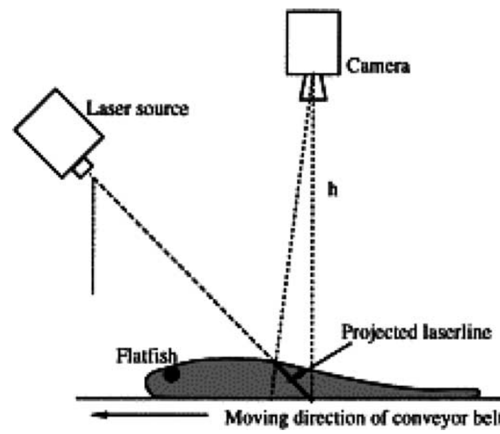

Fig. 6. Schematic of computer vision system for evaluating the volume of fish on a conveyor belt (Storbeck & Daan, 2001).

The development of automatic fish sorting techniques using image analysis has been investigated to reduce tedious human inspection and costs (Strachan & Kell, 1995). In a recent study an image processing algorithm based on moment-invariants coupled with geometrical considerations for discrimination between images of three species of fish was developed (Zion, Shklyar, & Karplus, 1999). Fish species identification reached 100%, 89% and 92%, respectively, for grey mullet, carp and St. Peter fish for 124 samples examined at different orientations. In a similar study Storbeck and Daan (2001) measured a number of features of different fish species as they passed on a conveyor belt at a speed of 0.21 m/s perpendicular to the camera as shown in Fig. 6. A neural network classified the species from the input data with an accuracy of 95%.

Jamieson (2002) used an X-ray vision system for the detection of bones in chicken and fish fillets. This commercial system operates on the principle that the absorption coefficients of two materials differ at low energies allowing the defect to be revealed. The developed system has a throughput of 10,000 fillets per hour and can correctly identify remaining bones with an accuracy of 99%. Tao, Chen, Jing, and Walker (2001) also investigated the use of X-ray imaging and adaptive thresholding for the internal inspection of deboned poultry with findings indicating that the developed technique can implement thickness invariant image segmentation.

3.3. Vegetables

The necessity to be responsive to market needs places a greater emphasis on quality assessment resulting in the greater need for improved and more accurate grading and sorting practices. Computer vision has shown to be a viable means of meeting these increased requirements for the vegetable industry (Shearer & Payne, 1990).

Shape, size, colour, blemishes and diseases are important aspects which need to be considered when grading and inspecting potatoes. A study by Tao et al. (1995a) investigated the use of a Fourier based separation technique for shape grading potatoes. A shape separator was defined based on harmonics of the transform, resulting in 89% agreement between the vision system and human assessment. A machine vision system has also been developed for grading potatoes using a HSI (hue, saturation, and intensity) colour system (Tao et al., 1995a). The system was able to differentiate between good and greened potatoes with an accuracy of 90% by representing features with hue histograms and applying multi-variate discriminant techniques. An automatic potato sorting method based on two colour components related to tuber brightness and blemishes produced an 80% success rate when validated against human expertise (Guizard, Gravoueille, & Crochon, 1998). Wooten, White, Thomasson, and Thompson (2000) investigated the use of machine vision for the purpose of yield and grade monitoring when fitted to a sweet potato harvester. Classification rates as high as 84% were recorded for the separation of culls from saleable produce.

Discoloration of mushrooms is undesirable in mushroom houses and it reduces market value. The colour and shape of the cap is the most important consideration of fresh mushrooms. Computer vision has been applied for the automated inspection and grading of mushrooms (Heinemann et al., 1994). The features considered were colour, shape, stem cut and cap veil opening. Misclassification of the vision system averaged 20% and compared well with the analysis of two human inspectors. Vízhányó and Tillett (1998) analysed colour images to decipher between mechanical damage and diseases in mushrooms so that optimisation of handling practices may be achieved to maintain maximum quality. Recently similar research used mushroom images recorded by a machine vision system to recognise and identify discoloration caused by bacterial disease (Vízhányó & Felfoldi, 2000). A vectorial normalisation method was developed to decrease the effect of the natural discoloration of the mushroom surface and increase the differences in the image caused by disease. The method identified all of the diseased spots as 'diseased' and none of the healthy and senescent mushroom parts were detected as 'diseased'. The measurement of the developmental stage of mushrooms has also been examined by computer vision (Van Loon, 1996), with findings indicating that cap opening correlated the best with the stage of development. Reed, Crook, and He (1995) also used camera based technology to select mushrooms by size for picking by a mushroom harvester.

Machine vision has also been used in a variety of other quality assessment applications in the vegetable industry. Three image processing algorithms to recognise cabbage head and to estimate head size were developed for the construction of a selective harvester (Hayashi, Kanuma, Ganno K, & Sakaue, 1998). From the projected area the head size could be estimated in a processing time of 2.2 s with an error of between 8.6 and 17.9 mm. Two algorithms for analysing digital binary images and estimating the location of stem root joints in processing carrots were developed by Batchelor and Searcy (1989). Both algorithms were capable of estimating the stem/root location with a standard deviation of 5 mm, however the midpoint technique could feasibly attain speeds exceeding 10 carrots per second. Howarth and Searcy (1992) also classified carrots for forking, surface defects, curvature and brokenness. The classification of broccoli heads from the analysis of line scan images with the discrete Fourier transform was developed for assessing its maturity (Qui & Shearer, 1992). For the 160 observations from each of three broccoli cultivars, an accuracy of 85% was achieved for multiple cultivars. Tollner et al. (1999) line-scanned sweet onions for internal defects using X-ray imaging. The findings indicated that a neural classifier performed better than a Bayesian, with accuracies of 90% and 80% respectively for sorting onions into two classes.

3.4. Fruit

External quality is considered of paramount importance in the marketing and sale of fruits. The appearance i.e., size, shape, colour and presence of blemishes influences consumer perceptions and therefore determines the level of acceptability prior to purchase. The consumer also associates desirable internal quality characteristics with a certain external appearance. This learned association of internal quality to external quality affects future purchases (Wills, Graham, Mc Glasson, & Joyce, 1998). To meet the quality requirements of customer, computer vision is being implemented for the automated inspection and grading of fruit to increase product throughput and improve objectivity of the industry.

Computer vision has been used for such tasks as shape classification, defect detection, quality grading and variety classification. Defect segmentation on Golden Delicious apples was performed by CMV (Leemans et al., 1998). A colour model developed was used as a standard for comparison with sample images. The developed algorithm gave satisfactory results with well-contrasted defects, however two further enhancements following segmentation were required to improve accuracy. A novel adaptive spherical transform was developed and applied in a machine vision defect sorting system (Tao & Wen, 1999). The transform converts a spherical object image to a planar object image allowing fast feature extraction, giving the system an inspection capacity of 3000 apples/min from the three cameras, each covering 24 apples in the field of view. A 94% success rate was achieved for sorting defective apples from good ones for the 600 samples tested. Three major apple surface features were considered in a study by Yang (1993) using machine vision. Extracted features were used as inputs to neural network which gave an average classification accuracy of 96.6% for the separation of defective samples. Further studies by Yang (1994, 1996) reported the use of a flooding algorithm for defect detection and stem and calyx identification. Hue itself, and hue, saturation and intensity have also been used as a basis for the classification of Golden Delicious apples in studies by Heinemann, Varghese, Morrow, Sommer, and Crassweller (1995) and by Tao, Morrow, Heinemann, and Sommer (1995b). Both systems achieved over 90% accuracy for the inspection of the apples by representing features as histograms and by applying multi-variate discriminant analysis technique for classification.

Steinmetz et al. (1999) combined two non-destructive sensors to predict the sugar content of apples. A spectrophotometer and computer vision system implemented online resulted in an accuracy of 78% for the prediction of sugar content with a processing time of 3.5 s per fruit.

Analysis of the shape profile of apples using a Fourier expansion procedure was performed by Paulus and Schrevens (1999). These results were then compared to Fourier coefficients of profiles from an existing shape descriptor list. The first and second components were found to explain 92% of the total variance in the fruit. Fourier and Fourier inverse transform were used to describe Huanghua pear shape (Ying, Jing, Ma, Zhao, & Jiang, 1999). The first 16 harmonics of the Fourier descriptor represented the primary shape of the pea. The shape identification accuracy was 90% by applying the Fourier descriptor in combination with the artificial neural network. Dewulf, Jancsok, Nicolai, De Roeck, and Briassoulis (1999) used image-processing techniques to obtain the geometrical model of a Conference pear in a study using finite element modal analysis to determine its firmness.

In the research by Singh and Delwiche (1994) a monochromatic camera with a near infrared band pass filter was used to capture images of stone fruit for detecting and identifying major defects. Correlation coefficients between machine predicted and manually measured defects areas were 0.75 and 0.72 for bruise and scar, respectively. The detection of split pits in peaches was investigated using X-ray technology in association with computer vision (Han et al., 1992). A detection algorithm was developed based on a threshold equation and tested on 198 peaches with 98% identified correctly.

Kim and Schatzki (2000) investigated the use of 2-D X-ray imaging to detect internal water core damage in apples. A total of eight features were extracted from X-ray scanned apple images and classified using a neural network to categorise the apple samples. Apples were classified into clean and severe categories with 5–8% false positive and negative ratios with findings independent of apple orientation. Radiograms of whole apples were obtained with a line scanning X-ray systems at two different orientations in a study by Schatzki et al. (1997). Still images were viewed on screen with less than 5% of good apples classified as defective when examined for water core. However when images were scrolled across the screen simulating a three chain sorting line, recognition rates fell to unacceptable levels which were at half of that corresponding to a commercial sorting line.

The quality sorting of tomatoes was performed based on a two-sensor system, one for vision and the other for impact (Laykin et al., 1999). Image processing algorithms were developed to inspect colour, colour homogeneity, bruises, shape and stem detection. The combined sensor system yielded 88% exact classification with 95% of the fruit correctly classified. The concept of chaos such as attractor and fractal dimension was introduced to quantitatively measure and evaluate the irregularity (or regularity) of the tomato fruit shape (Morimoto, Takeuchi, Miyata, & Hashimoto, 2000). A one-dimensional profile data consisting of six profiles of each fruit was used. From the analysis of the attractor, there existed a close correlation between the ratio (X/Y) of the attractor (X, width; Y, length) and the irregularity of the one-dimensional profile data. The fractal dimension also increased with the irregularity of the data (fruit shape).

Sugar content and acid content of Iyokan orange fruit were evaluated using a machine vision system by Kondo, Ahmada, Montaa, and Muraseb (2000). Images of 30 Iyokan orange fruits were acquired by a colour TV camera. Features representing fruit colour, shape and roughness of fruit surface were extracted from the images. The correlation coefficient between measured sugar content values and predicted sugar content values was 0.84 while the correlation coefficients between measured pH values and predicted pH values was 0.83 for the developed system. Ruiz, Molto, Juste, Pla, and Valiente (1996) also used computer vision for the location and characterisation of stem calyx area on mechanically harvested oranges. Colour segmentation, contour curvature analysis and a thinning process were the image analysis techniques used in this study, yielding accuracies of 93%, 90% and 98% respectively, for stem absence or presence.

In order to offer the consumer a more uniform product, the separation and classification of mixed nuts into lots of uniform shape and size is desirable. Pearson and Toyofuku (2000) developed a non-invasive inspection method using machine vision for the identification and removal of pistachio nuts with closed shells from processing streams. This automated system had a throughput of approximately 40 nuts per second and an accuracy of 95% comparable with current mechanical devices without any of the damage associated with these mechanisms (Ghazanfari, Irudayaraj, & Kusalik, 1996; Pearson & Slaughter, 1996). Grey scale intensity profiles across the width of the pistachio nuts were used for the detection of early split (Pearson & Slaughter, 1996). The developed system classified early split nuts with 100% success and normal nuts with 99% accuracy out of a total of 180 nuts tested. Multi-structure neural network (MSNN) classifier was proposed and applied to classify four varieties (classes) of pistachio nuts (Ghazanfari et al., 1996). The performance of the MSNN classifier was compared with the performance of a multi-layer feed-forward neural network (MLNN) classifier. The average accuracy of the MSNN classifier was 95.9%, an increase of over 8.9% of the performance of the MLNN, for the four commercial varieties examined. X-ray imaging in combination with machine vision was used to detect pinhole damage in almonds (Kim & Schatzki, 2001). By processing scanned film images, pinhole damage had an 81% correct recognition ratio compared to 65% for line-scanned images. The computation rate, if implemented online, was estimated to be 66 nuts per second.

Visual features of raisins such as wrinkle edge density, angularity, elongation for the purpose of grading were analysed by computer vision (Okamura, Dewiche, & Thompson, 1993). The developed system accuracy was comparable to industrial standard air stream sorter but poorer than sight grading results.

Sorting of strawberries based on shape and size was performed using computer vision with accuracy of 98% reported for the developed system (Nagata, Cao, Bato, Shrestha, & Kinoshita, 1997). Cao et al. (1999) described a method of extracting shape and orientation of strawberries using a machine vision system. An $L^*a^*b^*$ colour model was used with findings indicating that results were not affected by the surrounding illumination and that the extracted features were a good basis for sorting and harvesting applications.

3.5. Prepared consumer foods

With numerous foods containing cheese available on the market the necessity for the evaluation of cheese functional properties continues to grow. Present inspections are tedious and subjective based on empirical and sensory assessments hence the use of computer vision has been implemented for these tasks. Trials by Wang and Sun (2001, 2002a, 2002b, 2002c) investigated meltability and browning properties of cheddar and Mozzarella cheeses under different cooking condition and different sizes of samples using machine vision. Cheese shred dimensions were determined from skeletonised images using syntactic networks in a study by Ni and Gunasekaran (1995). This technique was successful in recognising individual shred when two were touching or overlapping and results compared well with manual measurements.

Topping type, percentage and distribution are the factors which influence the attractive appearance and separate many different varieties of pizza available commercially. At present inspection of these quality attributes is performed manually, however Sun (2000) investigated the use of computer vision for the analysis of these features. A new region based segmentation technique was developed and an accuracy of 90% was found when topping exposure and topping evenness were examined. Fig. 7 shows an example of comparison between an original pizza image and the corresponding segmented image. In other trials computer vision and fuzzy logic were used for the classification of pizza bases, sauce spread distribution and topping evenness for determining acceptable and defective quality samples.

Yin and Panigrahi (1997) also used computer vision to evaluate the internal texture of French fries. A set of 150 sample images were categorised into normal and hollow classes by three algorithms. The co-occurrence matrix gave the best results with 100% accuracy.

3.6. Grain

Cereal quality requirements differ with respect to the end users such as the preparation of varieties of bread, cakes, cookies and pasta products. The current visual classification procedure is demanding, even for trained inspectors because of the wide variation in visual

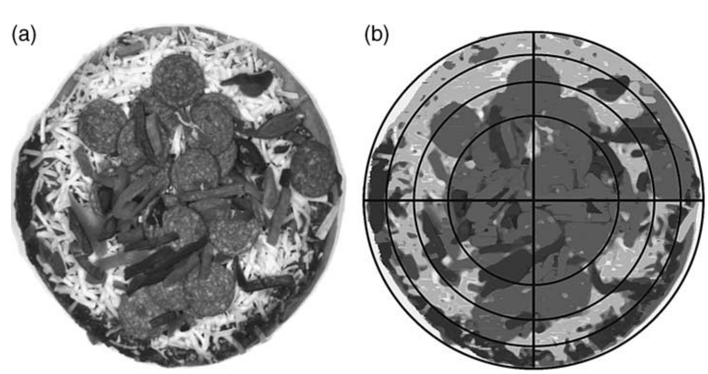

Fig. 7. Pizza images: (a) original image and (b) segmented image.

characteristics caused by contrasting class, varietal and environmental effects. Zayas et al. (1996) found that the physical characteristics of wheat could be used as the basis for the development of an objective wheat classification method. By the use of computer vision and crush force features, differentiation rate between hard and soft wheat was 94% for the varieties tested. A feature selection method based on an orthonormal transformation was used to discriminate digitised wheat cultivars (Uthu, 2000). Recognition of durum wheat cultivars and bread wheat cultivars was 82% and 81% respectively for the samples examined. In a comprehensive study Majumdar and Jayas (2000a, 2000b, 2000c, 2000d) investigated the use of morphology models, colour models, texture models and a combined model of all three for the classification of cereal grains. A total of 23 morphological, 18 colour, 25 textural features were tested on the training data set of 31,500 kernels. High accuracies were recorded for all the models examined ranging from 76% to 100%. The mean accuracies of the combined morphology–texture–colour model were 99.7% and 99.8% when tested on the independent and the training data sets of CWRS (Canada Western Red Spring) wheat, CWAD (Canada Western Amber Durum) wheat, barley, oats and rye. Similar research investigated the classification of dockage components from cereal grains and found that a morphology–colour model could classify test sample with a mean accuracy of 90.9% (Nair, Jayas, & Bulley, 1997).

Quality characteristics of corn have also been investigated by the use of computer vision. The classification of germplasms (ear of corn) was performed by use of an algorithm developed to discriminate round-shaped samples based on two features (Panigrahia, Misrab, & Willsonc, 1998). Two different approaches based on fractal geometry and higher order invariant moments were used for classification of non-round shaped germplasms. Fig. 8 shows the digitised image of a corn germplasms. This study found that both the fractal and invariant moment approaches have potential to be used for shape discrimination between cylindrical and non-cylindrical germplasms with an overall accuracy of 82.5% for this classification. A prototype machine vision

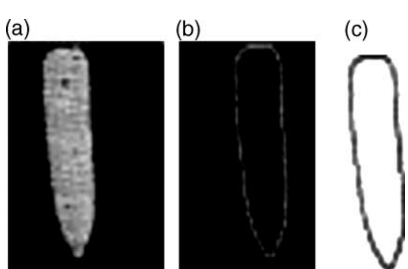

Fig. 8. Image processing of corn: (a) the digitised image of a corn germplasm, (b) the background removed image and (c) the extracted boundary of the image (Panigrahia et al., 1998).

system for automatically inspecting corn kernels was designed and tested by Ni, Paulsen, Liao, and Reid (1997). Blur due to the motion of the kernels was eliminated by the use of a strobe light and successful classification rates of 91% and 94% were achieved for classification of whole and broken kernels. Other studies using computer vision have been successful in the measurement and classification of corn whiteness, and mechanical and mould damage in corn (Liu & Paulsen, 1997; Ng, Wilcke, Morey, & Lang, 1997).

Quality is the most important factor in rice used for consumption (Singhal, Kulkarni, & Rege, 1997). Rice millers grade rice quality for nutritional and economic considerations, and thus need a fast and accurate grading system. Wan, Lin, and Chiou (2000) developed an online automatic grain inspection system using machine vision. A total of 16 brown rice appearance characteristics related to kernel shape, colour, and defects were employed to study the rice quality recognition performances of three classification techniques. Sound, cracked, chalky, broken, immature, dead, off-type, broken, paddy and damaged brown rice kernels could be recognised and sorted by the system with an accuracy of 91% at a speed of over 1200 kernels/min. A modified dark field illumination technique was used for the computer vision inspection and estimation of the internal damage of rough rice (Cardarelli, Tao, Bernhardt, & Lee, 1999). The machine vision system was 91.5% successful for correctly categorising a test sample when compared to rice visually separated by trained plant pathologists.

3.7. Food container inspection

Food container inspection using optical systems has developed rapidly since the first practical machine was introduced by Heuft in 1982 (Wallin & Haycock, 1998). The progression since has resulted in the food container industry being ranked third as the end user of machine vision (Novini, 1995). Container inspection covers a large number of different areas. These include inspection of bottles for thread, sidewall and base defects, with returned bottles inspected by vision systems to determine shape and to check for foreign matter. Filled bottles are also inspected for fill level, correct closure and label position at an operating speed of up to 60,000 bottles per hour (Anon, 1995). A bottle cap inspection system used information feedback to help to reduce the number of defects produced, resulting in an reduction from 150 to 7 or 8 defects in an 8 h period (Whelan, 1991). Table 3 shows a comparison of the throughput of different online computer vision systems. Machine vision has also been used for the detection of wrinkles, dents or other damage to aluminium cans that may cause leakage of contents (Seida & Frenke, 1995).

Table 3
Throughput of selected online applications of computer vision

Area of use	Speed/processing time	Accuracy (%)	Reference
Pork lion chops	1 sample/s	90	Tan et al. (2000)
Fish identification	0.21 m/s conveyor	95	Storbeck and Daan (2001)
Detection of bones in fish and chicken	10,000/ h	99	Jamieson (2002)
Estimation of cabbage head size	2.2 s/sample	–	Hayashi et al. (1998)
Location of stem root joint in carrots	10/s	–	Batchelor and Searcy (1989)
Apple defect sorting	3000/min	94	Tao and Wen (1999)
Sugar content of apples	3.5 s/fruit	78	Steinmetz et al. (1999)
Pinhole damage in almonds	66 nuts/s	81	Kim and Schatzki (2001)
Bottle inspection	60,000/h	–	Anon (1995)

3.8. Other applications

Strickland (2000) reported the use of digital imaging technology for the automatic monitoring of dry sugar granules and powders. This system provides particle size data to production line operators for process control and product quality improvement.

4. Conclusions

This review presents the recent developments and applications of image analysis in the food industry, the basic concepts and technologies associated with computer vision. Image processing is recognised as being the core of computer vision with the development of more efficient algorithms assisting in the greater implementation of this technique. The automated, objective, rapid and hygienic inspection of diverse raw and processed foods can be achieved by the use of computer vision systems.

Computer vision has the potential to become a vital component of automated food processing operations as increased computer capabilities and greater processing speed of algorithms are continually developing to meet the necessary online speeds. The flexibility and non-destructive nature of this technique also help to maintain its attractiveness for application in the food industry. Thus continued development of computer vision techniques such as X-ray, 3-D and colour vision will ensue higher implementation and uptake of this technology to meet the ever expanding requirements of the food industry.

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