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Inspection and grading of agricultural and food products by computer vision systems—a review

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Abstract

Computer vision is a rapid, economic, consistent and objective inspection technique, which has expanded into many diverse industries. Its speed and accuracy satisfy ever-increasing production and quality requirements, hence aiding in the development of totally automated processes. This non-destructive method of inspection has found applications in the agricultural and food industry, including the inspection and grading of fruit and vegetable. It has also been used successfully in the analysis of grain characteristics and in the evaluation of foods such as meats, cheese and pizza. This paper reviews the progress of computer vision in the agricultural and food industry, then identifies areas for further research and wider application the technique.

Keywords: Computer vision; Food; Fruit; Grain; Image analysis and processing; Vegetables

1. Introduction

Computer vision is a relatively young discipline with its origin traced back to the 1960s (Baxes, 1994). Following an explosion of interest during the 1970s, it has experienced continued growth both in theory and application. Sonka et al. (1999) reported that more than 1000 papers are published each year in the expanding fields of computer vision and image processing. Applications of these techniques have now expanded to various areas such as medical diagnostic, automatic manufacturing and

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surveillance, remote sensing, technical diagnostics, autonomous vehicle and robot guidance.

Computer vision is the construction of explicit and meaningful descriptions of physical objects from images (Ballard and Brown, 1982). Timmermans (1998) states that it encloses the capturing, processing and analysis of two-dimensional images, with others noting that it aims to duplicate the effect of human vision by electronically perceiving and understanding an image (Sonka et al., 1999). The basic principle of computer vision is described in Fig. 1. Image processing and image analysis are the core of computer vision with numerous algorithms and methods available to achieve the required classification and measurements (Krutz et al., 2000).

Computer vision systems have been used increasingly in the food and agricultural industry for inspection and evaluation purposes as they provide suitably rapid, economic, consistent and objective assessment (Sun, 2000). They have proved to be successful for the objective measurement and assessment of several agricultural products (Timmermans, 1998). Over the past decade advances in hardware and software for digital image processing have motivated several studies on the development of these systems to evaluate the quality of diverse and processed foods (Locht et al., 1997; Gerrard et al., 1996). Computer vision has long been recognised as a potential technique for the guidance or control of agricultural and food processes (Tillett, 1990). Therefore, over the past 20 years, extensive studies have been carried out, thus generating many publications.

The majority of these studies focused on the application of computer vision to product quality inspection and grading. Traditionally, quality inspection of agricultural and food products has been performed by human graders. However,

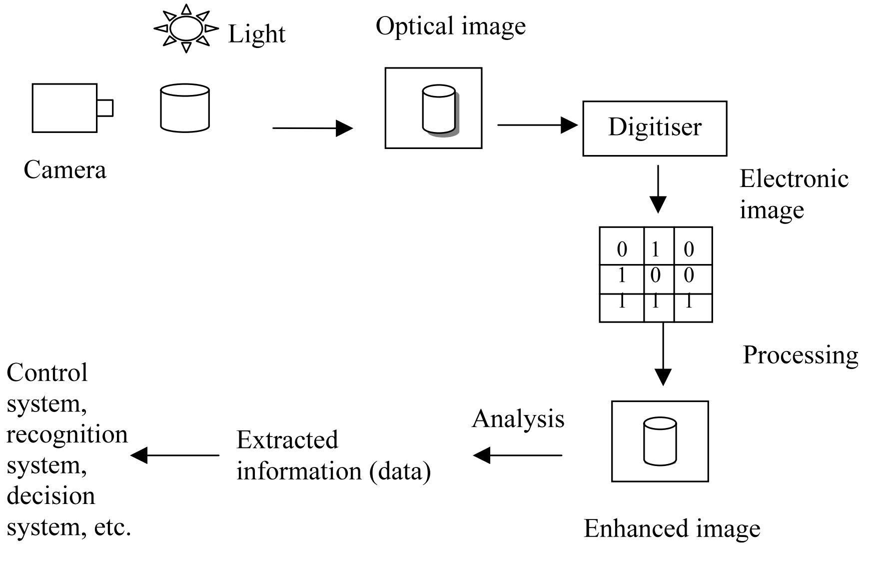


Fig. 1. Principle of computer vision system.

in most cases these manual inspections are time-consuming and labour-intensive. Moreover the accuracy of the tests cannot be guaranteed (Park et al., 1996). By contrast it has been found that computer vision inspection of food products, was more consistent, efficient and cost effective (Lu et al., 2000; Tao et al., 1995a). Also with the advantages of superior speed and accuracy, computer vision has attracted a significant amount of research aimed at replacing human inspection. Recent research has highlighted the possible application of vision systems in other areas of agriculture, including the analysis of animal behaviour (Sergeant et al., 1998), applications in the implementation of precision farming and machine guidance (Tillett and Hague, 1999), forestry (Krutz et al., 2000) and plant feature measurement and growth analysis (Warren, 1997).

Besides the progress in research, there is increasing evidence of computer vision systems being adopted at commercial level. This is indicated by the sales of ASME (Application Specific Machine Vision) systems into the North American food market, which reached 65 million dollars in 1995 (Locht et al., 1997). Gunasekaran (1996) reported that the food industry is now ranked among the top ten industries using machine vision technology. This paper reviews the latest development of computer vision technology with respect to quality inspection in the agricultural and food industry.

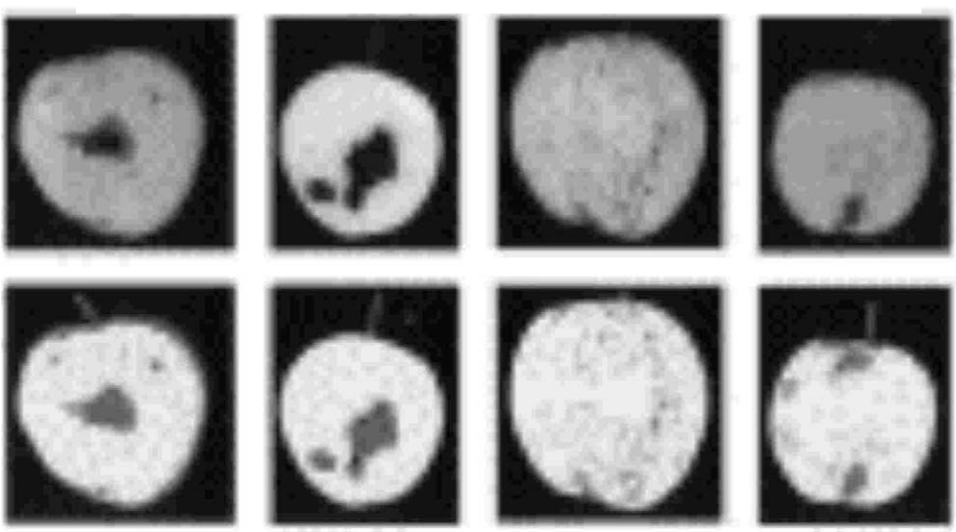
2. Assessment of fruits and nuts

Computer vision has been widely used for the inspection and grading of fruits. It offers the potential to automate manual grading practices and thus to standardise techniques and eliminate tedious inspection tasks. Kanali et al. (1998) reported that the automated inspection of produce using machine vision not only results in labour savings, but can also improve inspection objectivity.

2.1. Apples

The study of apples using computer vision has attracted much interest and can reflect the progress of computer vision technology for fruit inspection. Computer vision has been used for such tasks as shape classification, defects detection, quality grading and variety classification. Paulus and Schrevens (1999) developed an image-processing algorithm based on Fourier expansion to characterise objectively the apple shape so as to identify different phenotypes. In this research it was shown that four images per apple were needed to quantify the average shape of a randomly chosen apple. It was found that this profile analysis can be used to characterise existing shape descriptor lists, e.g. of ideal apples as defined by the International Board for Plant Genetic Resources. Hence it links existing subjective shape descriptors and objective measurements of shape recognition. Experimentation by Paulus et al. (1997) also used Fourier analysis of apple peripheries as a quality inspection/classification technique. This methodology gave insight into the way in which external product features affect the human perception of quality. The research found that as the classification involved more product properties and became more complex, the error of human classification increased.

Leemans et al. (1998) investigated the defect segmentation of 'Golden Delicious' apples using machine vision. To segment the defects, each pixel of an apple image was compared with a global model of healthy fruits by making use of the Mahalanobis distances. The proposed algorithm was found to be effective in detecting various defects such as bruises, russet, scab, fungi or wounds. Fig. 2 shows the results of sample apple images segmented by the three algorithms applied sequentially in this study. In similar studies Yang (1996) assessed the feasibility of using computer vision for the identification of apple stems and calyxes which required automatic grading and coring. Back propagation neural networks were used to classify each patch as stem/calyx or patch-like blemish. An overall accuracy of 95% was reported for the 69 Golden Delicious and 55 Granny Smith samples examined. Earlier studies proposed the use of a 'flooding' algorithm to segment patch-like defects (russet patch, bruise, and also stalk or calyx area) (Yang, 1994). It was found that this method of feature identification is applicable to other types of produce with uniform skin colour. This technique was improved by Yang and Marchant (1995), who applied a 'snake' algorithm to closely surround the defects. To discriminate russet in 'Golden Delicious' apples a global approach was used and the mean hue on the apples was computed (Heinemann et al., 1995). A discriminant function sorted the apple as accepted or rejected. The accuracy reached 82.5%, which is poor compared with European standards (Heinemann et al., 1995). Other studies



(a) (b) (c) (d)

Fig. 2. Samples of apples with various defects segmented with three algorithms applied sequentially: (a) typical defect; (b) well-contrasted defect; (c) diffuse defect; and (d) bruise (Leemans et al., 1998).

involving 'Golden Delicious' apples were performed for the purpose of classification into yellow or green groups using the HSI (hue, saturation, intensity) colour system method (Tao et al., 1995a). The results show that an accuracy of over 90% was achieved for the 120 samples tested.

Steinmetz et al. (1999) investigated sensor fusion for the purpose of sugar content prediction in apples by combining image analysis and near-infrared spectrophotometic sensors. The repeatability of the classification technique was improved when the two sensors were combined giving a value of 78% for the 72 test samples. An online system with the use of a robotic device (Molto et al., 1997) resulted in a running time of 3.5 s per fruit for the technique.

2.2. *Oranges*

Computer vision has been applied to the classification of oranges by reference to their visual characteristics. Ruiz et al. (1996) studied three image analysis methods to solve the problem of long stems attached to mechanically harvested oranges. The techniques include colour segmentation based on linear discriminant analysis, contour curvature analysis and a thinning process which involves iterating until the stem becomes a skeleton. It was found that these techniques were able to determine the presence or absence of a stem with certainty, however, stem location was correctly estimated in 93, 90 and 98% for the different techniques, respectively, in the samples tested. A study by Kondo (1995) investigated the quality evaluation, i.e. by the correlation of appearance with sweetness, of Iyokan oranges using image processing so as to automate the orange classification operation. The results demonstrated that the method could effectively predict the sweetness of the oranges with a 87% correlation efficiency between measured and calculated sugar content obtained from neural networks.

2.3. *Strawberries*

Strawberry appearance and fruit quality are dependent on a number of pre- and post- harvest factors, hence variation occurs, necessitating the need for sorting. Nagata et al. (1997) investigated the use of computer vision to sort fresh strawberries, based on size and shape. The experimental results show that the developed system was able to sort the 600 strawberries tested with an accuracy of 94–98% into three grades based on shape and five grades on size. Another automatic strawberry sorting system was developed by Bato et al. (2000). Average shape and size accuracies of 98 and 100%, respectively, were obtained regardless of the fruit orientation angle with judgement time within 1.18 s.

2.4. *Nuts*

Mixing of pistachio nuts of different varieties and quality often occurs as a result of mixed plantations or during harvesting and handling, hence separation and classification must be performed. For the detection of early split lesions on the hull of pistachio nuts machine vision has been used (Pearson and 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. In other research a multi-structure neural network (MSNN) classifier was proposed and applied to classify four varieties (classes) of pistachio nuts (Ghazanfari et al., 1996). In this study, 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 of nuts tested with 150 samples in each. An automated machine vision system was developed to identify and remove pistachio nuts with closed shells from processing streams (Pearson and Toyofuku, 2000). The system included a novel material handling system to feed nuts to linescan cameras without tumbling. The classification accuracy of this machine vision system for separating open shell from closed shell nuts was approximately 95%, similar to mechanical devices. The system has a throughput rate of approximately 40 nuts per s comparable to colour sorters used to remove other pistachio defects.

2.5. Tomato

Tomato quality is primarily based on uniform shape and freedom from growth and handling defects. Nielsen et al. (1998) developed a technique to correlate the attributes of size, colour, shape and abnormalities, obtained from tomato images, with the inner quality of the tomato samples. They applied fuzzy sets into their study. Recently, chaos theory was introduced into this area (Morimoto et al., 2000). In this study tomato fruit shape was quantitatively evaluated using an attractor, fractal dimension and neural networks. The results showed that a combination of these three elements offers more reliable and more sophisticated classification. Computer vision has also been used in the assessment of tomato seedling quality as a classification technique to ensure only good quality seedlings were transplanted (Ling and Ruzhitsky, 1996). The classification process adopted an adaptive thresholding technique, the Oust method. The disagreement between canopy areas measured by manual examination and machine vision segmented, canopy portion boundaries, had a range from -2.6 to $+2.3$%.

2.6. Peaches and pears

As consumer awareness and sophistication increases the importance of objective measurement of quality is ever increasing. In a study by Miller and Delwiche (1989) the maturity of market peaches was evaluated by colour analysis. Their method was based on comparing peach ground colour with reference peach maturity colour to estimate the amount of blushed surface area. However, an accuracy of only 54% agreement with manual classification was achieved for the 160 peaches examined. This inaccuracy was a result of only two views of the peaches captured, i.e. some of surface not imaged and also because of errors in manual grading. A more recent study by Dewulf et al. (1999) combined image processing with a finite element model to determine the firmness of pears. The application of computer vision technology to detect pear bruising was studied by Zhang and Deng (1999). Results from the experiments confirmed that different bruised areas can be precisely detected with most relative errors controlled to within 10%.

2.7. Fruit harvesting

The automatic location of fruit in a harvesting scene is of added interest with developments in robotics and improvements in mechanised harvesting. The feasibility of using computer vision for this purpose was determined by Pla et al. (1993). To locate the fruit, the regions from a segmented image labelled as fruit colour were taken as the fruit position in the image. In tests of 19 images 95% of visible fruits were detected and a 6% failure rate. A vision algorithm for the guidance of a robotic cherry tomato harvester was developed by Kondo et al. (1996). This visual feedback control based harvesting method achieved a success rate of 70% for the 62 fruits attempted.

3. Vegetable inspection

3.1. Mushrooms

Computer vision has been shown to be a viable approach to inspection and grading of vegetables (Shearer and Payne, 1990). Heinemann et al. (1994) assessed the quality features of the common white Agaricus bisporus mushroom using image analysis in order to inspect and grade the mushrooms by an automated system. Of the 25 samples examined misclassification by the vision system ranged from 8 to 56% depending upon the quality feature evaluated, but averaged about 20%. The study also reported that disagreement between human inspectors ranged from 14 to 36%. Reed et al. (1995) found that computer vision could be combined with harvester technology to select and pick mushrooms based on size. Computer vision has also been applied to objective measurement of the developmental stage of mushrooms (Van Loon, 1996). This study found that cap opening of mushrooms correlated the best with the stage of development except for tightly closed mushrooms. Other research described the development of computer vision techniques for the detection, selection, and tracking of mushrooms prior to harvest (Williams and Heinemann, 1998).

From the spectral analyses on the colour of different mushroom diseases Vízhányó and Tillett (1998) concluded that the colour of the developed, senescent mushroom differs from any browning caused by diseases allowing earlier detection of infected specimens. Similar research developed a method, involving a series of complex colour operations, to distinguish the diseased regions of mushrooms from naturally senescing mushrooms (Vízhányó and Felfoldi, 2000). Intensity normalisation and image transformation techniques were applied in order to enhance colour differences in true-colour images of diseased mushrooms. The method identified all of the diseased spots as 'diseased' and none of the healthy, senescent mushroom parts were detected as 'diseased'.

3.2. Potatoes

Potatoes have many possible shapes which need to be graded for sale into uniform classes for different markets. This created difficulties for shape separation. A Fourier analysis based shape separation method for grading of potatoes using machine vision for automated inspection was developed by Tao et al. (1995b). A shape separator based on harmonics of the transform was defined. Its accuracy of separation was 89% for 120 potato samples, in agreement with manual grading. Earlier, Lefebvre et al. (1993) studied the use of computer vision for locating the position of pulp extraction automatically for the purpose of further analysis on the extracted sample. An image acquisition system was also constructed for mounting on a sweetpotato harvester for the purpose of yield and grade monitoring (Wooten et al., 2000). It was found that culls were differentiated from saleable sweetpotatoes with classification rates as high as 84%.

3.3. Others

Some other earlier studies of computer vision associated with vegetable grading and inspection include colour and defect sorting of bell peppers (Shearer and Payne, 1990). Morrow et al. (1990) presented the techniques of vision inspection of mushrooms, apples and potatoes for size, shape and colour. The use of computer vision for the location of stem/root joint in carrot has also been assessed (Batchelor and Searcy, 1989). Feature extraction and pattern recognition techniques were developed by Howarth and Searcy (1992) to characterise and classify carrots for forking, surface defects, curvature and brokenness. The rate of misclassification was reported to be below 15% for the 250 samples examined. More recently sweet onions were line scanned for internal defects using X-ray imaging (Tollner et al., 1999). An overall accuracy of 90% was achieved when spatial and transform features were evaluated for product classification.

4. Grain classification and quality evaluation

4.1. Wheat

Grain quality attributes are very important for all users and especially the milling and baking industries. Computer vision has been used in grain quality inspection for many years. An early study by Zayas et al. (1989) used machine vision to identify different varieties of wheat and to discriminate wheat from non-wheat components. In later research Zayas et al. (1996) found that wheat classification methods could be improved by combining morphometry (computer vision analysis) and hardness analysis. Hard and soft recognition rates of 94% were achieved for the seventeen varieties examined. Twenty-three morphological features were used for the discriminant analysis of different cereal grains using machine vision (Majumdar et al., 1997). Classification accuracies of 98, 91, 97,100 and 91% were recorded for CWRS (Canada Western Red Spring) wheat, CWAD (Canada Western Amber Durum) wheat, barley, oats and rye, respectively. 25 kernels per image were captured from a total of 6000 for each grain type examined.

The relationship between colour and texture features of wheat samples to scab-infection rate was studied using a neural network method (Ruan et al., 1997). It was found that the infection rates estimated by the system followed the actual ones with a correlation coefficient of 0.97 with human panel assessment and maximum and mean absolute errors of 5 and 2%, respectively. In this study machine vision-neural network based technique proved superior to the human panel. Image analysis has also been used to classify dockage components for CWRS (Canada Western Red Spring) wheat and other cereals (Nair et al., 1997). Morphology, colour and morphology–colour models were evaluated for classifying the dockage components. Mean accuracies of 89 and 96% for the morphology model and 71 and 75% for the colour model were achieved when tested on the test and training data sets, respectively. Overall 6000 kernels for each grain type were analysed. Machine vision was used to identify weeds commonly found in wheat fields in experimentation by Zhang and Chaisattapagon (1995). Five shape parameters were used in leaf shape studies and were found effective in distinguishing broadleaf weed species such as pigweed, thistle and kochia from wheat.

4.2. Corn

In order to preserve corn quality it is important to obtain physical properties and assess mechanical damage so as to design optimum handling and storage equipment. Measurements of kernel length, width and projected area independent of kernel orientation have been performed using machine vision (Ni et al., 1997a). The algorithm accuracy was between 0.86 and 0.89 measured by the correlation coefficient between predicted results and actual sieving for a 500 g sample. The processing time of the size-grading program was reported as being between 0.66 and 0.74 s per kernel. Steenhoek and Precetti (2000) performed a study to evaluate the concept of two-dimensional image analysis for classification of maize kernels according to size category. A total of 320 maize kernels were categorised into one of 16 size categories based on degree of roundness and flatness. Classification accuracy of both machine vision and screen systems was above 96% for round-hole analysis. However, sizing accuracy for flatness was less than 80%.

Ng et al. (1997) developed a machine vision algorithm for corn kernel mechanical and mould damage measurement, which demonstrated a standard deviation less than 5% of the mean value of the 250 grains examined. They found that this method was more consistent than other methods available. The automatic inspection of 600 corn kernels was also performed by Ni et al. (1997b) using machine vision. For whole and broken kernel identification on-line tests had successful classification rates of 91 and 94% for whole and broken kernels, respectively.

The whiteness of corn has been measured by an on-line computer vision approach by Liu and Paulsen (1997). For the 63 samples (50–80 kernels per sample) tested the technique was found to be easy to perform with a speed of 3 kernels per s. In other studies Xie and Paulsen (1997) used machine vision to detect and quantify tetrazolium staining in corn kernels. The tetrazolium-machine vision algorithm was used to predict heat damage in corn due to drying air temperature and initial moisture content.

4.3. Rice

As rice is one of the leading food crops of the world its quality evaluation is of importance to ensure it remains appealing to consumers. Liu et al. (1997) developed a digital image analysis method for measuring the degree of milling of rice. They compared the method with conventional chemical analysis and obtained a coefficient of determination of $R^2 = 0.9819$ for the 680 samples tested. Wan et al. (2000) employed three online classification methods for rice quality inspection:-namely range selection, neural network and hybrid algorithms. The highest recorded online classification accuracy was around 91% at a rate of over 1200 kernels/min. The range selection method achieved this accuracy but required time-consuming and complicated adjustment. In another study, milled rice from a laboratory mill and a commercial-scale mill was evaluated for head rice yield and percentage whole

Table 1
Summary of computer vision applications for the cereal industry

Product	Application	Reported accuracy	References
Wheat	Classification of types	94%	Zayas et al. (1996)
	Disease infection	0.97[a]	Ruan et al. (1997)
	Weed identification	–	Zhang and Chaisattapagon (1995)
Corn	Size	73–90%	Ni et al. (1997b)
	Whiteness	–	Xie and Paulsen (1997)
	Whole and broken kernel	91 and 94%	Ni et al. (1997a,b)
	Heat damage analysis	–	Xie and Paulsen (1997)
	Grading	80–96%	Steenhoek and Precetti (2000)
Rice	Degree of milling	0.98[a]	Liu et al. (1997)
	Grading	91%	Wan et al. (2000)
	Yield and percentage whole kernel	–	Lloyd et al. (2000)
Wheat, barley, oats, rye	Classification	98, 97,100 and 91	Majumdar et al. (1997)
	Dockage	90% (overall)	Nair et al. (1997)

[a] Reported correlation between computer vision system and normal assessment technique.

kernels, using a shaker table and a machine-vision system called the GrainCheck (Lloyd et al., 2000).

Table 1 shows an overview of the main products, applications, accuracies of the systems and references used in the cereal industry.

5. Applications in other food products

5.1. Pizza

Visual features such as colour and size indicate the quality of many prepared consumer foods. Sun (2000) investigated this in research on pizza in which pizza topping percentage and distribution were extracted from pizza images. A new segmentation algorithm was developed by combining three algorithms used to segment many different types of pizzas as the traditional segmentation techniques were found to be inadequate for this application. Fig. 3(a) and (b) shows a sample image before and after segmentation using the new algorithm. It was found that the new region-based segmentation technique could effectively group pixels of the same topping together. As the result, topping exposure percentage can be easily determined. The study reported that the accuracy of measuring the topping percentage by the new algorithm reached 90%.

5.2. Bakery products

Human perception based on visual inspection has long been recognised as a guide to quality assessment hence if the product fails to meet the customer's preconceptions the possibility of a purchase is greatly diminished. Consequently computer vision has been used in the assessment of confectionery products. Davidson et al. (2001) measured the physical features of chocolate chip biscuits, including size, shape baked dough colour, and fraction of top surface area that was chocolate chip using image analysis. Four fuzzy models were developed to predict consumer ratings based on three of the features. A prototype-automated system for visual inspection of muffins was developed by Zaid Abdullah et al. (2000). The colour of 100 light brown and 100 dark brown muffins was evaluated using the vision system and discriminant analysis compared with visual examination. The automated system was able to correctly classify 96% of pregraded and 79% of ungraded muffins. The algorithm procedure classified muffins to an accuracy of greater than 88%, compared with 20–30% variations in quality decisions amongst inspectors. Machine vision has also been used in the assessment of quality of crumb grain in bread and cake products (Sapirstein, 1995). Using this technique, analysis on the different characteristics influencing the crumb grain were studied.

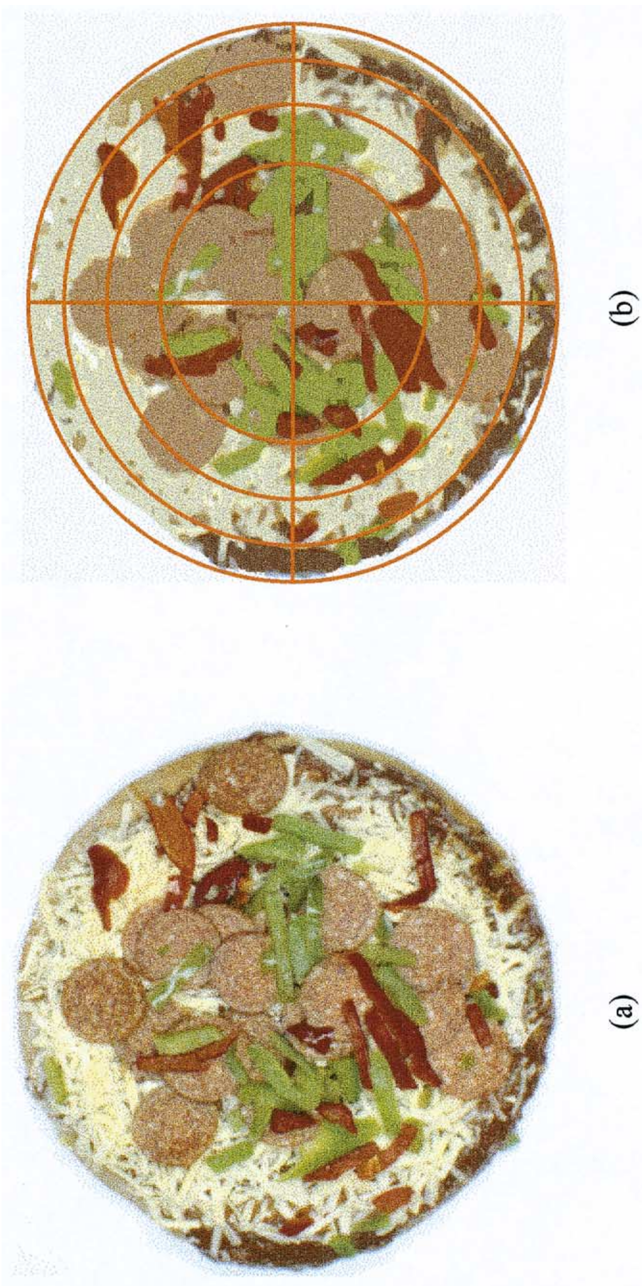


Fig. 3. Pizza images: (a) original image; (b) segmented image (Sun, 2000).

5.3. Cheese

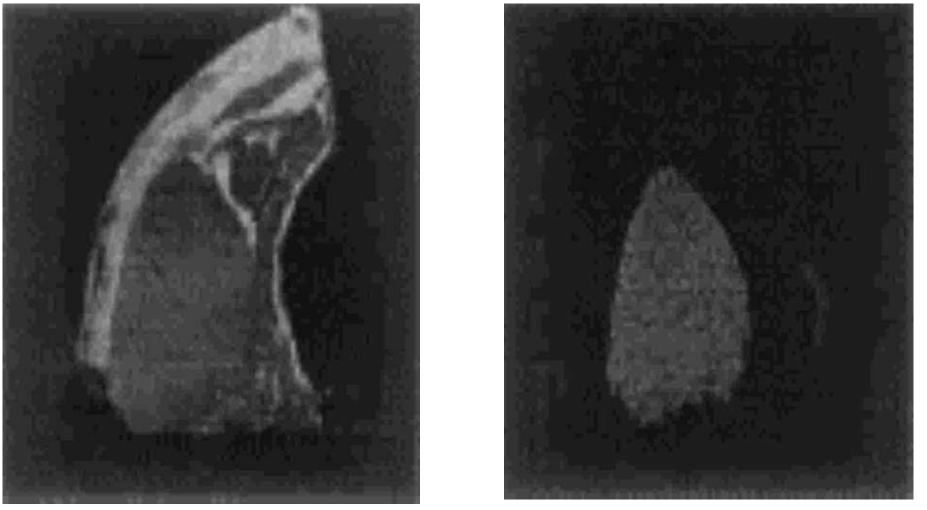
The evaluation of the functional properties of cheese is assessed to ensure the necessary quality is achieved, especially for specialised applications such as consumer food toppings or ingredients. Wang and Sun (2001) developed a computer vision method to evaluate the melting and browning of cheese. This novel non-contact method was employed to analyse the characteristics of cheddar and mozzarella cheeses during cooking and the results showed that the method provided an objective and easy approach for analysing cheese functional properties (Wang and Sun, 2002a,b). Ni and Gunasekaran (1995) developed an image-processing algorithm to recognise individual cheese shred and automatically measure the shred length. It was found that the algorithm recognised shreds well, even when they were overlapping. It was also reported that the shred length measurement errors were as low as 0.2% with a high of 10% in the worst case.

5.4. Meat and meat products

Visually discernible characteristics are routinely used in the quality assessment of meat. McDonald and Chen (1990) pioneered early work in the area of image based beef grading. Based on reflectance characteristics, they discriminated between fat and lean in the Longisimus muscle and generated binary muscle images. In a more recent study Gerrard et al. (1996) examined the degrees of marbling and colour in 60 steaks. The results showed that image processing effectively predicted the lean colour ($R_2 = 0.86$) and marbling scores ($R_2 = 0.84$). Image texture analysis has also been used in the assessment of beef tenderness (Li et al., 1997). Statistic regression and neural network were performed to compare the image features and sensory scores for beef tenderness and it was found that the texture features considerably contributed to the beef tenderness.

Evaluation of pork quality has also been investigated (Lu et al., 2000, 1997). The findings indicated that for 93% of the 44 pork loin samples, prediction error was lower than 0.6 in neural network modelling, hence it is recommended as an effective tool for evaluating fresh pork colour. Fig. 4 shows a pork loin and segmented images from these studies.

Gray-scale intensity, Fourier power spectrum, and fractal analyses were used as a basis for separating tumorous, bruised and skin torn chicken carcasses from normal carcasses (Park et al., 1996). A neural network classifier used performed with 91% accuracy for the required separation based on spectral images scanned at both 542 and 700 nm wavelengths. In a further study Park and Chen (2001) found that a linear discriminant model was able to identify unwholesome chicken carcasses with classification accuracy of 95.6% while a quadratic model (97% accuracy) was better to identify wholesome carcasses for the 176 carcasses examined. Earlier Daley et al. (1994) analysed chicken carcasses for systemic defects at a speed of 180 birds per min using global colour histograms based on a neural network classifier. The use of an X-ray inspection system for the detection of bones in chicken and fish was examined by Graves (Jamieson, 2002). This system called the 'Bonescan' exploits the fact that the



(a) (b)

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

absorption of coefficients of two materials are similar at high energies and so combine images obtained at high and low energies to differentiate bome from meat. The system with a throughput of 10,000 fillets per h was found to correctly identify remaining bones at an accuracy of 99%, while the fraction of chicked breasts or thighs that it incorreclty rejets is less than 3% (Jamieson, 2002).

5.5. Others

The focus of a study by Gunasekaran (1994) was to develop a computer vision based multi index active food shape feature extractor to minimum errors resulting from position and scaling. A statistical model based (SMB) feature extractor and a multi-index active model (MAM) based feature extractor were tested in conjunction with a multi-index classifier and a minimum intermediate zone (MIZ) classifier were used the extract the desired features from corn kernels, almonds and animal shaped crackers. The results showed that accuracy and speed were greatly improved when the MAM based feature extractor was used with the MIZ classifier. Yin and Panigrahi (1997) studied the internal texture of French fries using image techniques. Three computer vision algorithms were used to evaluate the hollowness with a resulting classification accuracy of 100% achieved. A study by Locht et al. (1997) examined the development of full colour machine vision analysis in the food industry. This WinGrain system analysed sirloin steak for fat content, chives for rust fungus, meat, pasta and rich dishes for component percentage composition and findings indicated that the system provides objective and quantifiable in-line visual information. The application of automated image analysis in the beverage industry was described by Braggins (2000). Computer vision was employed for the checking of wrap around sleeves on bottles, inspection of bottled champagne and beer keg inspection.

6. 3-D technique

In general, only 2-dimensional (2D) data are needed for grading, classification, and analysis of most agricultural images. However, in many applications 3-dimensional image analysis maybe needed as information on structure or added detail is required. A 3-D vision technique has been developed to derive a geometric description from a series of 2-D images (Sonka et al., 1999). In practice this technique might be useful for food inspection. For example, when studying the shape features of a piece of bakery, it is necessary to take 2-D images vertically and horizontally to obtain its roundness and thickness, respectively.

Recently Kanali et al. (1998) investigated the feasibility of using a charge simulation method (CSM) algorithm to process primary image features for three-dimensional shape recognition. The required features were transferred to a retina model identical to the prototype artificial retina and were compressed using the CSM by computing output signals at work cells located in the retina. An overall classification rate of 94% was obtained when the prototype artificial retina discriminated between distinct shapes of oranges for the 100 data sets tested. Gunasekaran and Ding (1999) obtained 3-D images of fat globules in cheddar cheese

Table 2
Advantages and disadvantages of computer vision

	References
Advantages	
Generates precise descriptive data	Sapirstein (1995)
Quick and objective	Liu et al. (1997)
Reduces tedious human involvement	Ni et al. (1997b)
Consistent, efficient and cost effective	Lu et al. (2000)
Automate many labour intensive processes	Gunasekaran (2001)
Easy and quick, consistent	Gerrard et al. (1996), Lefebvre et al. (1993)
Non-destructive and undisturbing	Tao et al. (1995a), Zayas et al. (1996)
Robust and competitively priced sensing technique	Gunasekaran and Ding (1993)
Permanent record, allowing further analysis later	Tarbell and Reid (1991)
Disadvantages	
Object identification is considerably more difficult in unstructured scenes	
Artificial lighting needed for dim or dark conditions	

from 2-D images. This enabled the in situ 3-D evaluation of fat globule characteristics so as the process parameters and fat levels may be changed to achieve the required textural qualities.

7. Advantages and disadvantages

Table 2 summarises the advantages and disadvantages of computer vision to different sectors of the agricultural and horticultural industries. The capabilities of digital image analysis technology to generate precise descriptive data on pictorial information have contributed to its more widespread and increased use (Sapirstein, 1995). Quality control in combination with the increasing automation in all fields of production has led to the increased demand for automatic and objective evaluation of different products. Sistler (1991) confirm that computer vision meets these criteria and states that the technique provides a quick and objective means for measuring visual features of products. In agreement it found that a computer vision system with an automatic handling mechanism could perform inspections objectively and reduce tedious human involvement (Morrow et al., 1990). Human grader inspection and grading of produce is often a labour intensive, tedious, repetitive and subjective task (Park et al., 1996). In addition to its costs, this method is variable and decisions are not always consistent between inspectors or from day to day (Tao et al., 1995a; Heinemann et al., 1994). In contrast Lu et al. (2000) found computer vision inspection of food products to be consistent, efficient and cost effective. Hence computer vision has been used widely in agricultural and horticulture to automate many labour intensive process (Gunasekaran, 2001). Even in 1993 Gunasekaran and Ding (1993) agreed that machine vision was becoming increasingly popular in the food industry, and pointed out that its development was at a level where it is a robust and competitively priced sensing technique. Yin and Panigrahi (1997) noted that cost effectiveness of computer vision technology for the food industry applications is constantly improving.

Computer vision is seen as an easy and quick way to acquire data that would be otherwise difficult to obtain manually (Lefebvre et al., 1993). Gerrard et al. (1996) recognised that machine image technology provides a rapid, alternative means for measuring quality consistently. Another benefit of machine vision systems is the non-destructive and undisturbing manner in which information is attained (Zayas et al., 1996), making inspection unique with the potential to assist humans involving visually intensive work (Tao et al., 1995b). Tarbell and Reid (1991) noted that an attractive feature of a machine vision system is that it can be used to create a permanent record of any measurement at any point in time. Hence archived images can be recalled to look at attributes that were missed or previously not of interest.

An ambiguity of computer vision is that its results are influenced by the quality of the captured images. Often due to the unstructured nature of typical agricultural settings and biological variation of plants within them, object identification in these applications is considerably more difficult. Also if the research or operation in being conducted in dim or night conditions artificial lighting is needed.

8. Conclusions

The paper reviews the recent developments in computer vision for the agricultural and food industry. Computer vision systems have been used increasingly in industry for inspection and evaluation purposes as they can provide rapid, economic, hygienic, consistent and objective assessment. However, difficulties still exist, evident from the relatively slow commercial uptake of computer vision technology in all sectors. Even though adequately efficient and accurate algorithms have been produced, processing speeds still fail to meet modern manufacturing requirements. With few exceptions, research in this field has dealt with trials on a laboratory scales thus the area of mechatronics has been neglected, and hence it needs more focused and detailed study.

The adaptation of computer vision for quality evaluation of processed foods is the area for the greatest potential uptake of this technology, as analysis can be based on a standard requirement in already automated controlled conditions. More complex systems are needed for the automated grading of fresh produce because of the greater range in variability of quality and also as produce orientation may influence results. With the idea of precision and more environmental friendly agriculture becoming more realistic the potential for computer vision in this area is immense with the need in field crop monitoring, assessment and guidance systems. However, techniques such as 3D and colour vision will ensure computer vision development continues to meet the accuracy and quality requirements needed in this highly competitive and changing industry.

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