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REVIEW PAPER

Advances in Machine Vision Applications for Automatic Inspection and Quality Evaluation of Fruits and Vegetables

Sergio Cubero · Nuria Aleixos · Enrique Moltó · Juan Gómez-Sanchis · Jose Blasco

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Abstract Artificial vision systems are powerful tools for the automatic inspection of fruits and vegetables. Typical target applications of such systems include grading, quality estimation from external parameters or internal features, monitoring of fruit processes during storage or evaluation of experimental treatments. The capabilities of an artificial vision system go beyond the limited human capacity to evaluate long-term processes objectively or to appreciate events that take place outside the visible electromagnetic spectrum. Use of the ultraviolet or near-infrared spectra makes it possible to explore defects or features that the human eye is unable to see. Hyperspectral systems provide information about individual components or damage that can be perceived only at particular wavelengths and can be used as a tool to develop new computer vision systems adapted to particular objectives. In-line grading systems allow huge amounts of fruit or vegetables to be inspected individually and provide statistics about the batch. In general, artificial systems not only substitute human inspection but also improve on its capabilities. This work presents the latest developments in the application of this technology to the inspection of the internal and external quality of fruits and vegetables.

Keywords Computer vision · Image analysis · Fruits and vegetables · Automatic inspection · Internal quality · Hyperspectral · In-line grading

S. Cubero · E. Moltó · J. Blasco (✉)
Centro de Agroingeniería, Instituto Valenciano de Investigaciones Agrarias,
Cra. Moncada-Náquera, Km. 5,
46113 Moncada, Spain
e-mail: blasco_josiva@gva.es

S. Cubero
e-mail: cubero_ser@gva.es

E. Moltó
e-mail: molto_enr@gva.es

N. Aleixos
Instituto Interuniversitario de Investigación en Bioingeniería y Tecnología Orientada al Ser Humano, Universidad Politécnica de Valencia,
Camino de Vera s/n,
46022 Valencia, Spain
e-mail: naleixos@dig.upv.es

J. Gómez-Sanchis
Intelligent Data Analysis Laboratory (IDAL), Electronic Engineering Department, Universitat de València,
Dr. Moliner 50,
46100 Burjassot (Valencia), Spain

Nomenclature

ANN	Artificial neural networks
ANOVA	Analysis of variance
BMP	Bitmap image format
CA	Correlation analysis
CART	Classification and regression trees
CCD	Charge-coupled device
CMOS	Complementary metal oxide semiconductor
CNN	Competitive neural networks
CT	Computed tomography
DA	Discriminant analysis
GALDA	Genetic algorithm based on LDA
HSI	Hue, saturation, intensity colour space
HSV	Hue, saturation, value colour space
JPG	Joint Photographic Experts Group image format
k-NN	k-nearest neighbour
L*a*b*	CIE-Lab colour space
LDA	Linear discriminant analysis
Luv	CIE-Luv colour space
MI	Mutual information

MIA	Multivariate image analysis
MRI	Magnetic resonance imaging
NIR	Near-infrared
PCA	Principal component analysis
PCI	Peripheral component interconnect
PLS	Partial least square
RGB	Red, green, blue colour space
sRGB	Standard RGB
SSC	Soluble solids content
SVM	Support vector machine
SW	Stepwise multivariate analysis
TA	Titratable acid
TIF	Tagged image file format
USB	Universal serial bus
UV	Ultraviolet
UVFL	Ultraviolet-induced fluorescence
XYZ	XYZ colour space

Introduction

The application of machine vision in agriculture has increased considerably in recent years. There are many fields in which computer vision is involved, including terrestrial and aerial mapping of natural resources, crop monitoring, precision agriculture, robotics, automatic guidance, non-destructive inspection of product properties, quality control and classification on processing lines and, in general, process automation. This wide range of applications is a result of the fact that machine vision systems provide substantial amounts of information about the nature and attributes of the objects present in a scene. Moreover, machine vision opens up the possibility of studying these objects in regions of the electromagnetic spectrum in which the human eye is not sensitive, as is the case of the ultraviolet (UV) or infrared regions (Zude 2008).

One field where the use of this technology has spread rapidly is the inspection of agri-food commodities (Sun 2007), including meat (Du and Sun 2009), fish (Quevedo et al. 2008a; Quevedo and Aguilera 2010) and particularly the automatic inspection of fruits and vegetables, since it is more reliable and objective than human inspection. The quality of a particular fresh or processed piece of fruit or vegetable is defined by a series of physicochemical characteristics which make it more or less attractive to the consumer, such as its ripeness, size, weight, shape, colour, the presence of blemishes and diseases, the presence or absence of fruit stems, the presence of seeds and its sugar content. These characteristics cover all of the factors that exert an influence on the product's appearance, on its nutritional and organoleptic qualities or on its suitability for preservation. Most of these factors have traditionally been assessed by visual inspection performed by trained operators, but nowadays, many of them are estimated with commercial vision systems (Du and Sun 2006).

As the decisions made by operators are affected by psychological factors such as fatigue or acquired habits, there is a high risk of human error in classification processes, and this is one of the most important drawbacks that can be prevented by automated inspection systems based on computer vision. A study carried out with different varieties of apples, where various shape, size and colour parameters were compared by trained operators, showed the limited human capacity to reproduce the estimation of quality, which the authors defined as 'inconsistency' (Paulus et al. 1997). Moreover, as the number of parameters considered in a decision-making process increases, so does the error of classification.

Computer vision can simplify tedious monitoring processes that take a long time or require complex apparatus to be performed. In this regard, Martynenko (2008) developed a computer vision system capable of estimating changes in the density and porosity of ginseng roots during drying, thus avoiding the need for complex scanning electron microscope imaging.

Nevertheless, automated inspection of agricultural produce shows certain particularities and problems that are not present in other fields due to their biological nature. While manufactured products often present similar colours, shapes, sizes and other external features, fruit and vegetables may show very different characteristics from one item to another. One single fruit can have a different colour, size and shape from another one, even though both of them were picked the same day from the same tree. Fruit and vegetables naturally change their colour or texture after being harvested, and these features depend on their maturity and how they are stored (ambient humidity and temperature, fungal diseases, presence of volatiles, duration of the storage, etc.). Furthermore, the colour on a particular area of the skin of a healthy fruit may match the colour of a blemish on the surface of another fruit of the same variety. Moreover, it is essential that the presence of stem-ends, leaves, dirt or any extraneous material be identified and not confused with true skin defects. On the other hand, markets demand very fast image processing, and for this reason, a trade-off between speed and accuracy must be found.

The aim of this article is to provide a comprehensive review of recent advances in computer vision applied to the inspection of fruits and vegetables. This includes the description of the different technologies used, together with the applications and current developments aimed at inspecting the internal parts of these commodities. We will discuss works based not only on visible image analysis but also on UV or near-infrared (NIR) imaging. Hyperspectral image analyses are also the foundations of new applications. Moreover, new image sources, such as those produced by magnetic resonance (MR) or X-rays, allow researchers to widen the scope of fruit and vegetable inspection to their internal quality characteristics.

This article is organised as follows. A description of current lighting systems and image acquisition methods is covered in 'The Basics of Machine Vision Systems' section. 'Applications of Computer Vision in the Inspection of External Features' section describes general applications related to the analysis of external quality features of fruits and vegetables, such as colour, size, shape, texture and detection of external defects. The next section deals with the 'Inspection of the Internal Quality'. 'Real-Time Automatic Inspection Systems' section gives an overview of automation and in-line inspection. Finally, the last section shows the 'Conclusions' of this review and the expected trends in computer vision applied to the analysis of fruits and vegetables.

The Basics of Machine Vision Systems

The success of an application for the inspection of fruits or vegetables depends on the quality of the images that are acquired, which largely depends on two factors: the camera and the illumination. While the camera relies mostly on advances in technology, it is the researcher who must decide how to build the illumination system, depending on the particular application and the geometry of the object to be inspected.

Lighting

In the external quality assessment using machine vision, a good lighting system should provide uniform radiation throughout the scene, avoiding the presence of glare or shadows, and it must be spectrally uniform and stable over time. If the scene is adequately illuminated for a particular purpose, image pre-processing is less necessary, thus saving processing time.

The arrangement of the light sources affects the acquired images: some areas may receive more light than others, which changes the total amount of radiation reflected by the objects in these areas. Uneven illumination can be corrected by calibrating with the inclusion of a white plate of known reflectance in the image (white reference), but this correction does not always work as desired and consumes computational resources. Moreover, it is very important to take into account the geometry of the objects to be inspected when designing the illumination. Lamps situated at a vertical angle of 45° with respect to a flat object are commonly effective. In this case, specular reflection is reduced, thereby avoiding unwanted glare. This configuration was used by Fernandez et al. (2005) to illuminate apple slices in order to control and evaluate their dehydration by tracking their colour and shape. A similar system was later used by Pedreschi et al. (2006) to illuminate potato chips in a system designed to measure the kinetics of colour changes under different frying temperatures.

On the other hand, if the object is almost spherical, it is more convenient to use a hemispherical diffuser chamber in order to illuminate the scene uniformly. Riquelme et al. (2008) used such a chamber to illuminate and inspect olives. However, in these systems, and in those in which the object is illuminated from above, the top of the object may appear brighter than the borders, thus creating a false change of colour that later has to be corrected. Gómez-Sanchis et al. (2008b) proposed a methodology for correcting this effect in citrus fruits by constructing an elevation model of the fruit and using it to estimate the theoretical height of a pixel and the angle of incidence of the light for each pixel. This made it possible to estimate appropriate corrections of the observed reflectance. Figure 1 shows examples of possible lighting systems to illuminate spherical and flat objects.

Spot light sources, particular object shapes and the presence of natural waxes on the surface of many fruits and

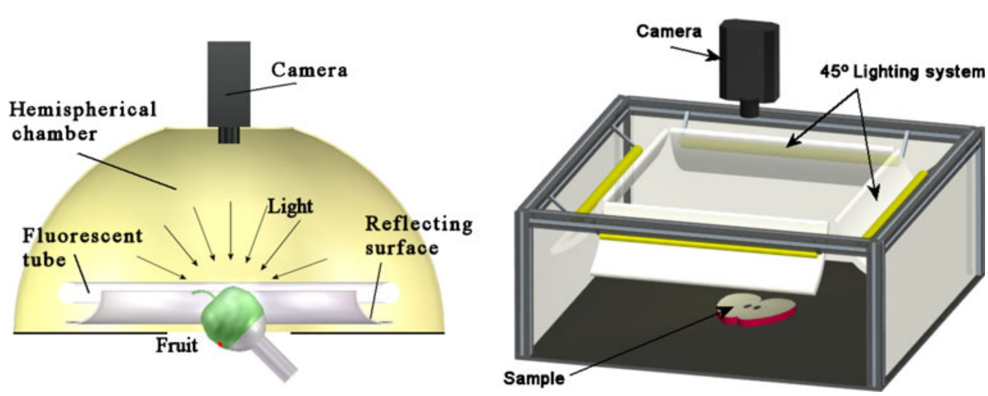

Fig. 1 Examples of diffuse lighting and directional lighting oriented 45° from the sample

vegetables enhance specular reflections of the light produced by the lamps. In such cases, some areas of the scene reflect most of the radiation generated by the source, which modifies the spectral reflectance that the object would show when illuminated by a diffuse, non-punctual source. This alters the colours in the corresponding area in the image and hinders the detection of defects. Diffused light-emitting systems and cross-polarised filters prevent the appearance of specular reflection in the images. An example of a technique to avoid bright spots in images of citrus fruits illuminated by fluorescent tubes is shown by Blasco et al. (2007a).

When the object to be inspected is translucent or when its contour has to be defined in the image with precision, many authors use backlighting, which is to say the object is situated between the light source and the camera. This solution was adopted by Blasco et al. (2009a) for in-line inspection of mandarin segments travelling over semi-transparent conveyor belts. By illuminating the segments from behind, segments in the images showed a sharp contrast with the background, which made it easier to estimate their size and shape. At the same time, seeds appeared darker than the rest of the segment, which facilitated their detection.

The emission spectrum of the source is crucial for adequate image acquisition. Fluorescent tubes are suitable for applications in which visible light is important (i.e. colour sorting) but produce less radiation in the infrared region. Moreover, they produce a characteristic flickering that is generally corrected by using high-frequency electronic ballasts. Incandescent lamps emit more infrared radiation, but normally generate a lot of heat, can be considered punctual sources and have a low colour temperature, which is an important drawback for applications based on colour.

Lighting systems based on light-emitting diodes (LEDs) are becoming cheaper and more frequent. They normally have low energy consumption and produce little heat but, on the other hand, they are very directional, and illumination power is still limited.

A special mention of lighting systems that induce fluorescence must also be made. Specific short wavelength (high energy) light excites certain molecules, and the subsequent relaxation produces lower energy (longer wavelength) light. Induced fluorescence allows some kinds of external damage to be detected. UV sources may be either fluorescent tubes or mercury vapour lamps. These induce visible fluorescence (550–500 nm) on molecules of essential oils present in the skin after cell breakage. Chlorophyll fluorescence was employed by Obenland and Neipp (2005) to locate incipient peel injury caused by hot water treatment in lemons. Visible- and UV-induced fluorescence (UVFL) was also used by Ariana et al. (2006a) to detect different types of defects in three varieties of apples. The emission of 740 nm light after UV excitation allowed them to detect all the defects under study. Slaughter et al. (2008) used the same method to detect freeze damage, which is difficult to achieve under visible lighting. Success rates between 64% and 88%, depending on the severity of the damage, were reported. Another application of UVFL is the detection of contaminants in fruits, as described by Lefcout and Kim (2006), who employed this technique to detect faeces on apples and found that 668 nm is the peak of the fluorescence response of faeces.

Image Acquisition

Digital cameras convert the light that they receive from the scene into electronic signals. Different image acquisition devices can be found in the literature. The most popular industrial cameras are based on charge-coupled device (CCD), which consists of an array of sensors (pixels), each of which is a photocell and a capacitor (Peterson 2001). The load acquired by the capacitor depends on the amount of light received by the photocell. These charges are converted into a voltage and subsequently converted into a video signal. Some cameras are based on a linear CCD array, composed of a one-dimensional array of cells, which acquire a narrow strip of the scene. These cameras, known as line-scan cameras, are suitable for applications where the object moves below the camera or the camera moves above the object, so that the complete image of its surface is gradually acquired, line by line.

Matrix cameras are the most widespread in commercial applications. They acquire a scene by using a two-dimensional CCD array. Colour cameras can be constructed with a single colour CCD array, composed of pixels that are sensitive to the primary red, green and blue (RGB) bands, but more sophisticated higher quality 3-CCD cameras are now available. In these cameras, light that enters through the primary lens is divided into three parts by a series of lenses and mirrors, thus generating three copies of the scene—one is directed towards a red filter, one to a green filter and the third to a blue filter. These filters are followed by a monochrome CCD sensor, so each CCD acquires one of the RGB signals.

Newer cameras are based on complementary metal oxide semiconductor (CMOS) sensors. The increase in the density of the integration of semiconductors has enabled this technology to develop rapidly. These sensors have a lower energy consumption and lower manufacturing costs, and so currently, they are widely applied in webcams.

Sometimes, the inspection of natural products requires image acquisition systems that are sensitive to visible and invisible wavelengths. Multispectral cameras combine several visible and invisible, not necessarily narrow, bands using appropriate filters and sensors. Aleixos et al. (2002)

developed a multispectral camera to obtain visible and NIR images of the same scene of citrus fruits in an automated sorting machine. Lleó et al. (2009) used a camera that was sensitive at three visible and NIR bands to estimate the maturity of peaches. Throop et al. (2005) proposed a special camera, designed to acquire images at 740 and 950 nm in combination with visible imaging, to classify apples in real time. Unay and Gosselin (2006) used four interference band-pass filters centred on 450, 500, 750 and 800 nm to detect defects in apples.

More recently, systems for the acquisition of hyperspectral images have also become available for fruit and vegetable inspection (Sun 2010). They use narrow band filters to generate *n*-dimensional images composed of *n* monochrome images, each of them corresponding to a specific wavelength. Depending on the technology, hyperspectral acquisition systems can be classified, being the most popular systems: imaging spectrographs (Polder et al. 2003), acousto-optical tunable filters (AOTF; Bei et al. 2004) and liquid crystal tunable filters (LCTF; Evans et al. 1998).

Imaging spectrographs separate the reflection of a very thin slice of the scene into its spectral components by using a prism or a grate and project the spectral information onto an imaging sensor, typically a CCD or CMOS line-scan camera (Kim et al. 2001). An AOTF is an optical band-pass filter based on diffraction that can be rapidly tuned to discrete wavelengths by varying the frequency of an acoustic wave propagating through an anisotropic crystal medium. LCTF is a birefringent filter, which uses the phase retardation between the ordinary and extraordinary light rays passing through a liquid crystal to create a constructive and a destructive interference, thus passing a single wavelength (Stratis et al. 2001). All these systems can be sensitive up to about 2,500 nm, and it is very important that both the spectrograph or filter and the camera are sensible in the same spectral range.

Examples of applications of hyperspectral systems are presented by Nilcolaï et al. (2006), who found particular types of damage to apples in the infrared region, and Karimi et al. (2009), who studied the changes in reflectance (350 to 2,500 nm) of avocados coated with different formulations. However, incorporating hyperspectral cameras in commercial packing houses is currently very complicated due to the high computational cost required by the acquisition and processing of these images.

Thermal cameras acquire mid-infrared images that can be related to the differences in the temperature in the scene and can therefore be used to monitor some agricultural processes (Vadivambal and Jayas 2010). The latest cameras are based on microbolometer arrays: when infrared radiation (8–13 μm) reaches their individual detectors, they heat and change their electrical resistance. These cameras using microbolometer arrays produce high-resolution images without requiring sensor cooling as the previous ones did (Hongchen et al. 2005).

The growth in computational power has boosted the use of high-resolution images, which results in an increase in the performance of machine vision systems. Nowadays, it is possible to detect defects as small as a few square millimetre. Another important advance is related to the implementation of high-speed protocols for data transfer between cameras and computers, like universal serial bus (up to 480 Mbps), FireWire (400 Mbps) or Giga-Ethernet (1,000 Mbps), which are much faster than the previously used frame grabbers on peripheral component interconnect buses (133 Mbps). These advances have modified the traditional architecture of a video camera connected to a frame grabber in a computer to the new architecture in which there is a direct communication between the camera and the computer. Smart cameras incorporate a microprocessor with an operating system on top of which the user can develop image-processing software, so that the camera becomes independent from the computer. Internet has increased the availability of the so-called IP cameras that transfer the images to a computer using transmission control protocol/IP and allow their remote control from a computer.

However, not only cameras are used for image acquisition in agricultural applications. Flatbed scanners have also been employed to acquire images of small objects like nuts or leaves (Menesatti et al. 2008). Pallottino et al (2010) determined the quality of hazelnut peeling by image processing using this technology. Moreover, medical equipment for internal diagnosis, based on X-rays or nuclear MR, has also been used to inspect the internal quality of fruits and vegetables (Hernández-Sánchez et al. 2007; Milczarek et al. 2009).

If the images need to be stored for later processing, the format in which they are stored can affect the subsequent image processing. Compressed formats like Joint Photographic Experts Group take advantage of the inherent limitations of the human eye and discard invisible information, thus making them useful in applications where memory size is a relevant issue. However, this format reduces the information available in the image and generates noise that can complicate subsequent image processing. Formats that do not reduce image quality, such as Tagged Image File format or Bitmap image format, are advisable for applications in which the loss of information is a factor that cannot be neglected.

Applications of Computer Vision in the Inspection of External Features

The ultimate purpose of many inspection systems based on computer vision is to estimate one or several features of the product of interest in a particular moment and relate them with the quality, which is normally associated to maturity, absence of deformities and blemishes, and so forth. Other systems are aimed at determining the evolution of the product over time in order to determine whether a particular treatment or process is valid or not.

In most of these applications, image analysis is employed to assess features like colour, size, shape, texture and presence of damage. In this chapter, we present some of the recent research on computer vision for the evaluation of fruit quality.

Use of Colour Information

Colour is one of the most important attributes for biological products, since consumers may be influenced to choose or reject a particular fruit by its colour. Producers therefore strive to prevent products with defective colorations from reaching the market, as well as ensuring that individual products are packed in batches with a similar colour. The colour is often measured using colorimeters (Hoffman 2010). Colour coordinates provided by these devices are often referred to as the CIE 1931 colour space, in which they are denoted by X, Y and Z. Colorimeters are limited to the measurement of small regions or in applications where the integration of the colour all over the sample is of interest, which means that they are not well suited to measuring objects with a heterogeneous colour (Gardner 2007). When it is necessary to measure the colour of large areas or the sample presents different colours that need to be discriminated, a still or video camera is required, since they provide images in which the colours of the pixels are determined individually.

The colour of a pixel in an image is expressed as three coordinates in a colour space. Spaces based on the primary colours red, green and blue (RGB) are the most widely used in computers and digital images. When inspected objects have different colours, sometimes a simple ratio can discriminate them, thus saving processing time. For instance, Blasco et al. (2009c) used RGB ratios to discriminate four categories of pomegranate arils. They used the average colour coordinates of each aril to classify them in real time. Tests showed that discriminate analysis applied to the RGB coordinates provided the same results as a simple threshold of the R/G ratio, both reaching a success rate in the classification of the arils higher than 90%. However, this last method was easier to implement and reduced processing time.

It is important to remark that RGB colour spaces are device-dependent (different devices produce different RGB values for the same pixels in a scene). For this reason, different approaches have been developed to standardise values, like the so-called standard RGB (sRGB) colour space (Stokes and Anderson 1996). Other spaces, closer to the human perception of colour, like the hue, saturation and intensity (HSI) space, are also commonly used in food inspection. Blasco et al. (2007b) compared five colour spaces for the identification of external defects in citrus fruits and obtained better results with HSI. Both RGB and HSI were used by Xiaobo et al. (2007) to classify Fuji apples in four colour categories. Frequently, individual HSI coordinates provide simple means for colour segmentation. Abdullah et al. (2006) converted RGB into HSI coordinates and used the H component to classify starfruits in four maturity categories.

However, RGB or HSI are non-uniform colour spaces. This means that the same Euclidian distance between two points in different regions of these spaces does not produce the same difference of perception in a standard observer. Uniform spaces like CIE 1,976 L*a*b* and Hunter L,a,b have been defined (HunterLab 2008). They are often used for colour comparison (León et al. 2006). Different colour spaces, such as sRGB, hue, saturation, value and L*a*b* were compared in terms of their suitability for colour quantification in curved surfaces. The last was found to be the most appropriate (Mendoza et al. 2006).

Simple algorithms based on a single L*a*b* coordinate are also used for fruit classification. The a* coordinate was used by Liming and Yanchao (2010) in grading strawberries attending three colour categories. Compared to human sorting, the system based on image analysis achieved 89% of success. Hue angle and chroma are colour features derived from the above-mentioned uniform spaces. Kang et al. (2008) quantified the effect of curvature on the calculation of hue angle and chroma and demonstrated that the hue angle provided a valuable quantitative description of the colour and colour changes of individual and batches of heterogeneously coloured mangoes.

Sometimes, it is important to measure how post-harvest treatments affect the colour of fruits. For instance, mandarins undergo a degreening treatment if harvested when they have not reached their typical orange colour. In these cases, fruits are stored in a chamber with a specific ethylene concentration and humidity. The duration of this treatment depends on the colour of the skin at harvest, expressed as a standard colour index (Jiménez-Cuesta et al. 1981). Fathi et al. (2009) used a still camera to measure the influence of different osmotic treatments of kiwifruit on their colour. They converted the original RGB coordinates to L*a*b* in order to assess colour differences and then used artificial neural networks to predict the colour changes caused by different osmotic treatments. Colour often also reveals symptoms of internal injuries in apples (Xul et al. 2009).

Computer vision also has outdoor applications, one of them being yield estimation. In these cases, colour is sometimes not the most important feature to be assessed.

Okamoto and Lee (2009) distinguished green citrus fruits on the trees from leaves with a similar colour. Since this is difficult to achieve using only visible information, they employed hyperspectral images in the 369–1,042-nm range. Safren et al. (2007) also proposed a machine vision-based method for automating yield estimation of Golden Delicious apples on trees at different growth stages, using visible and NIR hyperspectral imaging. A similar objective was pursued by Bulanon et al. (2009) in citrus, but they used a different approach based on combining visible and thermal images. They employed two image fusion approaches that improved fruit detection and proved to perform better than using thermal images alone.

Size and Volume Estimation

Size is particularly important in industry as a means of classifying objects in different commercial categories. The price of many agricultural products is directly related with their size. Measurement of this attribute in spherical or quasi-spherical objects is relatively easy, but it becomes more and more complex in irregularly shaped fruit and vegetables. The features most commonly used to estimate size are area, perimeter, length and width. However, due to the natural irregularities in the shape of agricultural produce, these measurements frequently depend on the orientation of the object with respect to the camera. For this reason, many authors combine size information obtained from images taken from different relative angles between the object and the camera. For instance, Blasco et al. (2003) estimated the size of Golden Delicious apples from four images of the fruit, and size was calculated from the view in which the stem was located nearest to the centroid of the object. Throop et al. (2005) measured the size of 14 cultivars of apple on fruits travelling on rollers by adjusting their translational and rotational speeds in such a way that images of one complete revolution of each fruit were captured regardless of their size. In this work, equatorial diameter and area of the apple were first calculated, then the apple was modelled as an ellipse, and height was estimated from its major axis. This sizing was used later for orienting the fruit and surface analysis.

Volume is also used as an indirect measurement of size, but it is a particularly complex challenge to estimate volume from a flat image. In the scientific literature, one of the most frequently cited ways to estimate the volume of axi-symmetric agricultural products using computer vision is by subdividing the object into elementary areas or volumes. The image-processing method consisted in obtaining the contour of the object from a flat projection and dividing it into vertical sections. Revolving half of the height of each vertical section around the x-axis, slices of the object are obtained. On joining these slices together, the volume can be estimated. Using this theory, the volume of watermelon was determined by Koc (2007) and compared with that obtained using a traditional water displacement method. He found that the difference between the volumes estimated by image processing and water displacement was not statistically significant ($P>0.05$).

Shape Estimation

Fruits and vegetables are expected to have a particular shape. Products with deformations or strange shapes cannot be sold or have lower prices, and automatic inspection of fruit and vegetable quality must take this fact into account. This attribute is estimated from measurements of different features, depending on the typical shape of the species or varieties. For instance, Liming and Yanchao (2010) defined four shape classes of strawberries: long-taper, square, taper and rotundity. They extracted linear sequences from the fruit contour, normalised their length to eliminate the influence of the size and employed the k-means method to assign each fruit to a class. Sweet tamarind pods were sorted by Jarimopas and Jaisin (2008) into straight, slightly curved, curved and broken.

Circularity is another feature that has been used to characterise the shape of fruits (Unay and Gosselin 2007). These authors combined it with other statistical and textural features to classify Jonagold apples. The aspect ratio and ellipsoid ratio were used by Sadrnia et al. (2007) to estimate the shape of watermelons. In this work, mass, volume, dimensions, density, spherical coefficient and geometric mean diameter were calculated, and correlation coefficients between them were used to generate a model to determine whether a particular fruit had a standard shape or not.

High contrast images can be obtained using backlighting, where the object is silhouetted against the background thus making the shape easier to define. Costa et al. (2009) placed Tarocco oranges laterally on an illuminated dashboard to determine their shape. They extracted the polar signature of the contour and calculated Fourier harmonic coefficients to describe the size, shape and orientation of each fruit. Menesatti et al. (2008) also used backlighting to estimate the shape of hazelnuts in order to discriminate among different cultivars. Elliptic Fourier analysis was used to extract shape features that were analysed using a partial least square (PLS) model aimed at cultivar discrimination. Similar work was done by Antonucci et al. (2010) in discriminating among almond cultivars. This technique was also used by Blasco et al. (2009a) to obtain high contrasted images of Satsuma mandarin segments in a sorting machine. Shape descriptors, such as circularity, roundness, compactness, area, length, symmetry, elongation and Fourier descriptors obtained from the polar signature, were calculated from the contour in order to separate broken segments from sound ones.

Texture

Perception of a particular colour by a computer vision system can be different if the surfaces of the objects have different textures. For this reason, the study of texture is often integrated within studies of colour differences, including those to detect the presence of external defects. Texture can play an important role in image segmentation, thus making it an effective tool for pattern recognition problems, one of which is the automatic inspection of fruit and vegetables.

Segmentation based on pixel-oriented techniques (those that process individual pixels, without considering their neighbourhood) is quite sensitive to noise or local particularities in the scene. Texture-based segmentation requires more complex algorithms that take into account colour and space relationships between neighbouring pixels in order to characterise individual regions in an image and to detect changes between them (Blasco et al. 2007a).

Sometimes, fruits or vegetables belonging to the same variety have a high rate of texture and colour variability that complicates image analysis. Figure 2a illustrates how regions of images of citrus of the same cultivar (cv. Valencia) have similar colour and textural properties even though they belong to different sound and damaged areas. López-García et al. (2010) proposed a method that combines colour and texture information in a principal component analysis (PCA) model for the detection of skin defects in four cultivars of citrus. For this purpose, they used the RGB values of each pixel and those of their neighbourhood (in 3×3 and 5×5 windows). They detected 91.5% of all the defects in four varieties of oranges and mandarins with only 3.5% of false detections (Fig. 2b).

Colour co-occurrence matrices and their mathematical features are a common way to describe texture. Pydipati et al. (2006) used this method to determine whether texture-based HSI colour features could be used in conjunction with statistics to identify diseased and normal leaves of citrus trees under laboratory conditions. Normal and diseased citrus leaf samples with greasy spot, melanose and scab were evaluated. A similar method was described by Zhao et al. (2009) to differentiate sound skin and five other different types of damage in grapefruit images acquired under a microscope. Menesatti et al. (2009) used the so-called contrast, homogeneity, angular second moment and correlation from grey-level co-occurrence matrices to assess the starch content of apples, which is related to their ripeness. They used visible and NIR images in the 1,000–1,700-nm range. ElMasry et al. (2007) assessed ripeness of strawberries from pseudo-RGB images (constructed from monochrome images at 450, 500 and 650 nm). Overripe fruits had a rougher texture than unripe ones.

Less conventional approaches use fractal texture features derived from spectral Fourier analysis. An example of such work is that described by Quevedo et al. (2008b), who monitored the ripening of bananas by detecting the senescence spotting of the peel.

Detection of External Defects

Detection of skin defects and damage is the most widely extended application of image analysis to the inspection of fruit and vegetables. The presence of external damage is a clear sign of the lack of quality of a product. Many applications aimed at such detection have been described. One difficulty that is common to most of them is that of distinguishing defective areas of the fruit or vegetable from natural organs like calyxes or stems. Bennedsen et al. (2005) described an image-processing system to avoid this confusion in apples. This system minimised false positives by analysing multiple images acquired while the apples were rotating. Images were captured with two optical filters centred at 740 and 950 nm. Xing et al. (2007) identified several visible and NIR wavelengths that could be used to discriminate the stem-end and calyx from sound peel and

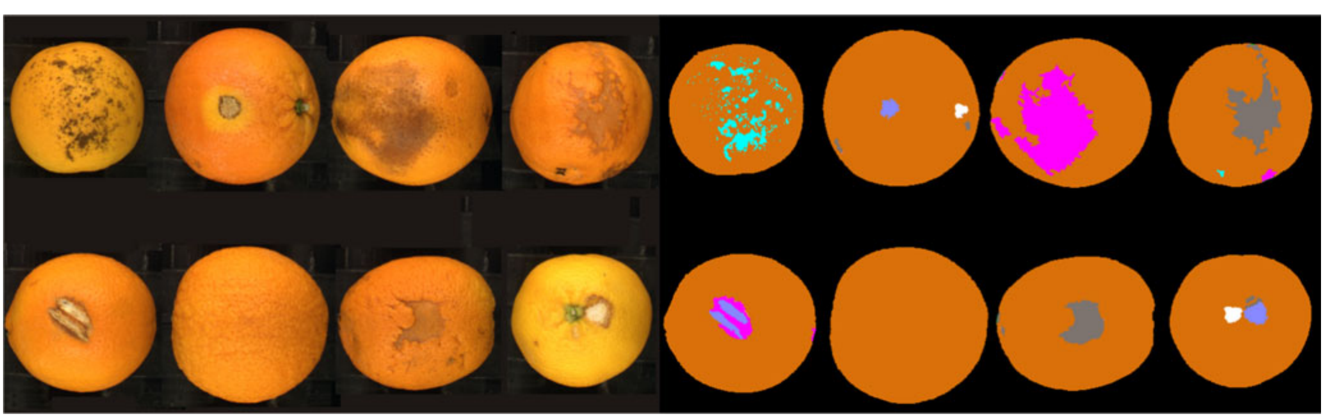

Fig. 2 *Left*: image of oranges showing skins with different defects, colours and textures. *Right*: same image segmented showing the defects found

bruises in apples by means of a hyperspectral system. They used PCA to reduce the highly dimensional spectral reflectance data to a few optimal wavebands. Unay and Gosselin (2007) compared different classification algorithms (based on linear discriminant analysis, k-nearest neighbours, fuzzy nearest neighbours and support vector machines) to recognise stem-ends and calyxes in sound and defective Jonagold apples. Since this variety presents a two-colour skin, they used four filters centred in the visible and NIR wavelengths.

Although some defects simply depreciate the commercial value of the fruit and do not evolve, others may prevent the fruit from being sold, may grow and appear during transport or storage, or may contaminate fruits and vegetables that were initially sound (i.e. fungal infestations). Those belonging to this second group must be detected as soon as possible to avoid the spread of rottenness. In these cases, detection of blemishes alone is not enough, and individual identification of the types of damage is necessary for an adequate post-processing. Blasco et al. (2007a) used a region-growing algorithm to separate contrasted regions of citrus fruits. These regions were subsequently merged using colour distances in the HSI colour space with the aid of an unsupervised algorithm. Figure 3 shows different steps of the iterative region-growing algorithm. This work allowed 11 different types of defects to be detected, but did not identify them. A later work combined spectral information from colour, NIR, UV and UVFL images to identify these defects (Blasco et al. 2007b). More recently, results were clearly improved by adding morphological parameters and decision algorithms (Blasco et al. 2009b).

As a continuation of the work mentioned above, Unay and Gosselin (2006) compared several methods (*k*-means, competitive neural networks and self-organising feature maps) to segment different types of defects in multispectral images automatically in real time.

Ariana et al. (2006a) integrated multispectral reflectance and fluorescence imaging for defect detection in three varieties of apples. Eighteen images of each apple were acquired using a combination of filters ranging from the visible to the NIR, using three imaging sources (reflectance-R, visible light-induced fluorescence (VFL) and UVFL). They used pixel level classification algorithms to distinguish between normal tissue and tissues affected by bitter pit, black rot, decay, soft scald and superficial scald.

Detection of bruises and rottenness before they become apparent has been the major objective of research on the automatic inspection of fruit and vegetable quality in the last few years. The potential of multispectral imaging

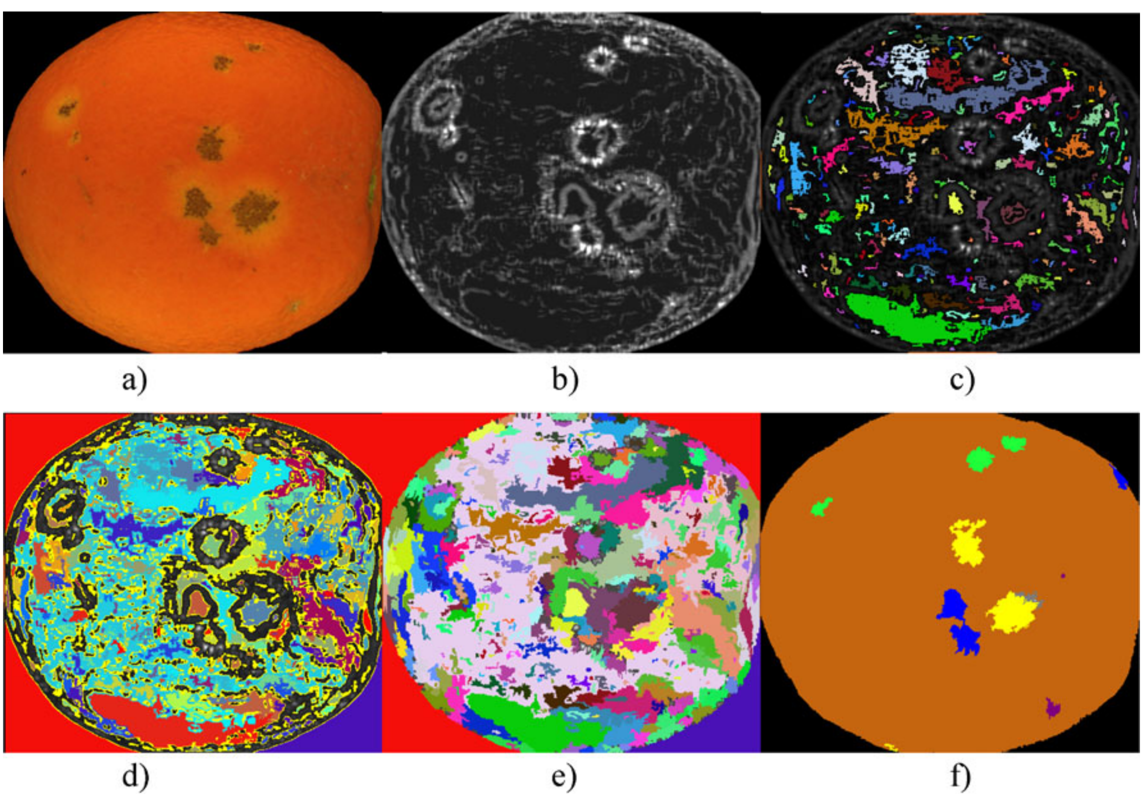

Fig. 3 Region-growing process to detect defects in citrus fruits. **a** Original colour image of an orange with blemishes caused by phytotoxicity. **b** Map of homogeneous colour regions where to locate the seeds. **c**, **d** Iterative growing steps. **e** Final growing step. **f** Final image after region-merging based on colour information

systems for early detection of bruises in McIntosh apples was investigated by ElMasry et al. (2008). They analysed the spectral reflectance between 400 and 1,000 nm, and PLS and stepwise discrimination analysis were used for data dimensionality reduction and selection of wavelengths. They chose three of them (750, 820 and 960 nm) to simulate a multispectral imaging system and demonstrated that bruised apples can be successfully distinguished from sound apples in the early stages of development of the blemishes. Later, they obtained five optimal wavelengths to detect chilling injury in Red Delicious apple using artificial neural networks (ElMasry et al. 2009).

Early detection of fungal rottenness of citrus using conventional colour cameras is difficult because the colour and texture of sound and infected peel are similar. However, images taken at some specific wavelengths present a high contrast between the sound and the affected skin. Figure 4 (top) shows images of oranges with different defects, acquired with a standard visible monochromatic camera and with a hyperspectral imaging system. Certain wavelengths (Fig. 4, bottom) enhance the appearance of the damage, which simplifies its detection by an automatic inspection system. Gómez-Sanchis et al. (2008a) used hyperspectral images to detect damage caused by *Penicillium digitatum* to citrus, and in the same work, they showed several examples of dimensionality reduction techniques and discrimination algorithms that can be employed.

Other applications of hyperspectral systems have been profusely cited in recent literature. Gowen et al. (2009) classified whole undamaged and freeze-damaged white button mushrooms. Ariana et al. (2006b) used them to find optimal bandwidths for detecting damage caused to pickling cucumbers by mechanical harvesting and handling systems. Qin et al. (2009) detected citrus canker, greasy spot, insect damage, melanose, scab and wind scar by means of the spectral information divergence classification method. This procedure was based on quantifying the spectral similarities using a predetermined canker reference spectrum in the spectral region from 450 to 930 nm. Blemishes on potatoes were detected by Barnes et al. (2010) using different features based on statistical information related to colour and texture which was optimised by means of an adaptive boosting algorithm.

Another non-conventional imaging approach to defect identification is the one described by Slaughter et al. (2008), who detected freeze-damaged Californian navel oranges using the UV fluorescence properties of the peel oil constituents. Table 1 show a summary of inspection systems for the external inspection of fruit and vegetables.

Inspection of the Internal Quality

Current technology allows scientists to acquire detailed images of the internal parts of fruits and vegetables that can be used for quality assessment. MR devices generate powerful magnetic fields capable of aligning the hydrogen nuclei of the water present in different tissues. Radio frequency fields are used to alter this alignment and make nuclei rotate and emit radio waves that that can be detected by an antenna. The manipulation of this signal by additional magnetic fields makes it possible to construct an image showing the internal structure of a fruit or vegetable (Hills 1998).

Milczarek et al. (2009) developed an in-line method to detect damaged pericarp tissue of tomatoes using multivariate analysis of MR images. The technique proved to be effective for predicting the conductivity score of pericarp

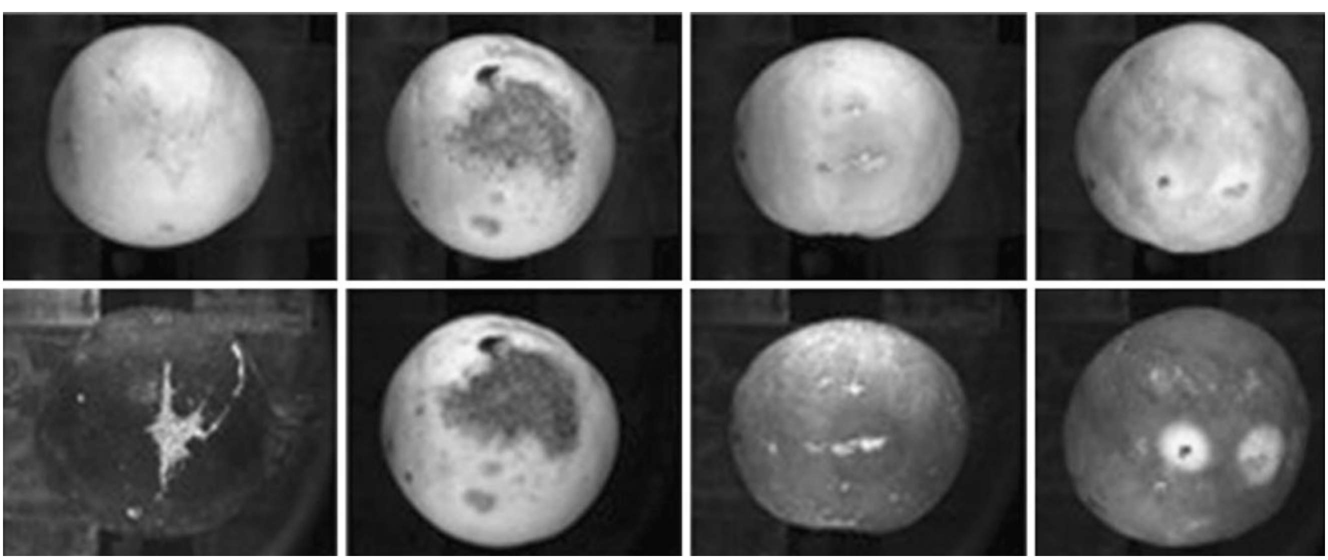

Fig. 4 Images of citrus fruits with different external defects acquired with a B/W monochromatic camera (*top*) and the same fruit acquired at a particular wavelengths (*bottom*). *From left to right*: 450, 720, 520 and 480 nm

Table 1 Summary of inspection systems for fruit and vegetables

Fruit	Imaging system	Focus on (colour coordinates and/or data processing methods in brackets)	References
Apple	CCD camera UVA fluorescent tubes, tungsten halogen lamp	Defects (ANN)	Ariana et al. (2006a)
	Imaging spectrograph 400–1,000 nm, halogen lamps 45°	Defects (PLS, SW)	ElMasry et al. (2008)
	Imaging spectrograph 430–900 nm, UV lamps 45°	Defects (ANN)	ElMasry et al. (2009)
	Imaging spectrograph 430–900 nm, directional UV lamps, fluorescence	Defects (histogram)	Lefcout and Kim (2006)
	Imaging spectrograph 430–900 nm, diffuse halogen lamps	Defects (PLS)	Lefcout et al. (2006)
	Imaging spectrograph 1,000–1,700 nm, directional halogen 45°	Colour (RGB), texture (starch, k-NN, PLSDA)	Unay and Gosselin (2007)
	CCD camera, directional fluorescent ring	Colour (RGB, HSI; GA)	Xiaobo et al. (2007)
	Imaging spectrograph 400-1,000nm, halogen lamps	Stem-calyx detection (PCA)	Xing et al. (2007)
Banana	Photographic camera, Diffuse fluorescent 45°	Texture (fractal Fourier descriptors)	Quevedo et al. (2008b)
	Photographic camera, diffuse fluorescent tubes 45°	Colour (sRGB, HSV, L*a*b*)	Mendoza et al. (2006)
Citrus fruits	3-CCD camera, fluorescent tubes with polarising filters	Colour (RGB, HSI), defects (region growing)	Blasco et al. (2007a)
	3-CCD camera, fluorescent tubes with polarising filters, black light, halogen lamps	Colour (RGB, HSI, Luv, Lab, XYZ), defects (LDA)	Blasco et al. (2007b)
	RGB camera+microscope	Defects (from texture), texture (colour co-occurrence, SW)	Zhao et al. (2009)
	3-CCD camera, fluorescent tubes with polarising filters, black light, halogen lamps	Colour (RGB, HSI), shape (area and Fourier descriptors), defects (LDA)	Blasco et al. (2009b)
	3-CCD camera, fluorescent tubes with polarising filters	Defects (MIA)	López-García et al. (2010)
Cucumber	Imaging spectrograph 950–1,350 nm, halogen lamps	Defects (PCA, band ratio, band difference)	Ariana et al. (2006b)
Grapefruit	Imaging spectrograph 450–930 nm, halogen lamps	Spectral information divergence	Qin et al. (2009)
Lemon	CCD camera UV lamps	Defects (thresholding)	Obenland and Neipp (2005)
Mandarin	Hyperspectral LCTF 460–1,020 nm, halogen lamps	Defects (SW, GALDA, CA, MI, CART, LDA)	Gómez-Sanchis et al. (2008a)
	Hyperspectral LCTF 460–1,020 nm, halogen lamps	Shape (digital elevation)	Gómez-Sanchis et al. (2008b)
Mango	Photographic camera, diffuse fluorescence	Colour (L*a*b*)	Kang et al. (2008)
Mushroom	Imaging spectrograph 450–950 nm	Colour (L), defects (PCA, LDA)	Gowen et al. (2009)
Olives	CCD camera	Colour (RGB, HSV), defects (ANOVA)	Riquelme et al. (2008)
Orange	Photographic camera, backlighting	Shape (Fourier descriptors, *k*-means)	Costa et al. (2009)
	Photographic camera, UV lamps 365 nm	Defects (thresholding)	Slaughter et al. (2008)
Peach	Multispectral camera, halogen lamps	Maturity, defects (clustering R/NIR)	Lleó et al. (2009)
Potato		Defects (AdaBoost)	Barnes et al. (2010)
Potato chips	Photographic camera, diffuse fluorescent 45°	Colour (L*a*b*)	Pedreschi et al. (2006)
Star fruits	CCD camera, fluorescent ring	Colour (H), shape (Fourier descriptors)	Abdullah et al. (2006)
Watermelon	CCD camera	Volume	Koc (2007)

tissue in tomatoes with a processing time of between 400 and 1,200 ms per image. Barreiro et al. (2008) studied different MR sequences to detect the presence of seeds in mandarins, the accuracy being 100% using a radial–spiral sequence. Figure 5 shows MR images of a mandarin with one seed inside acquired using different MR sequences. Internal browning of pears was also detected using MR images by Hernández-Sánchez et al. (2007), who compared MR relaxometry and MR imaging.

Light backscattering can also be used to assess internal quality features related to maturity or tissue texture. Baranyai and Zude (2009) studied the rotation of the intensity profiles in backscattering images of kiwis produced by changing the anisotropy of tissues during ripening. Significant differences were found between the anisotropy of premium quality kiwis and overripe pieces. Internal tissue firmness is very difficult to estimate from conventional external images. However, Peng and Lu (2008) evaluated different mathematical models for describing hyperspectral (450–1,000 nm) scattering profiles used for predicting the fruit firmness and soluble solids content (SSC) of Golden Delicious apples.

Laser-induced chlorophyll fluorescence scattering images were used by Noh and Lu (2007) to estimate flesh colour, firmness, SSC, and titratable acid (TA) using a hyperspectral imaging system. The fruit was illuminated by a continuous-wave blue (408 nm) laser at six different excitation times. A hybrid method, involving the combination of PCA and neural network modelling, was used to predict fruit quality parameters. Fluorescence emission decreased steadily during the first 3 min of illumination and became stable after 5 min. Good results were obtained for skin hue measurements, and relatively good predictions were obtained for fruit firmness, skin chroma and flesh hue. Poorer correlations were found for SSC, TA and flesh chroma.

A similar technique was employed by Qing et al. (2007). Images of backscattered light on the fruit surface were obtained from apples using laser diodes, emitting at five wavelengths (680, 780, 880, 940 and 980 nm). Corrected intensity frequency was used to estimate SSC and flesh firmness of apples grown at different locations and stages of maturation (Qing et al. 2008).

Thermography is still expensive because of the high price of the cameras, but it can be an alternative to assess the internal quality of fruits and vegetables. It was employed by Baranowski et al. (2008) to detect apple watercore. The time derivative of apple temperature per unit of mass was a good parameter to distinguish between apples with and without affected tissues. The rates of temperature increase per unit of mass were considerably lower for damaged apples, particularly in the initial stages of heating. Moreover, a good correlation was found between this parameter and fruit density.

Hyperspectral imaging systems have also been used to assess internal quality features. ElMasry et al. (2007) used such images to estimate the moisture content (MC), SSC and TA of strawberries. They employed PLS regression to obtain different sets of optimal wavelengths for each of these quality attributes. Table 2 shows a summary of works about the internal quality of fruits and vegetables estimated using image analysis.

Real-Time Automatic Inspection Systems

Fruits and vegetables travel at a high speed under the camera in current inspection lines in packinghouses. In order to acquire images with sufficient quality, cameras freeze the movement by using high-speed electronic shutters that are combined with adequate illumination, because as the shutter speed increases, the intensity of lighting must also increase to avoid underexposure. Moreover, progressive-scan cameras produce non-interlaced images, which also reduce blurring, and the two technologies are combined in most of the applications in this field.

In order to inspect the whole surface of the product, many current solutions rotate and move it under the camera, some use mirrors and others use several cameras that acquire different views of the product. Depending on the size of the object that has to be inspected and the required resolution, each image can be composed of a single object or a group. In the latter case, the position of each individual should also be recorded, since a sorting

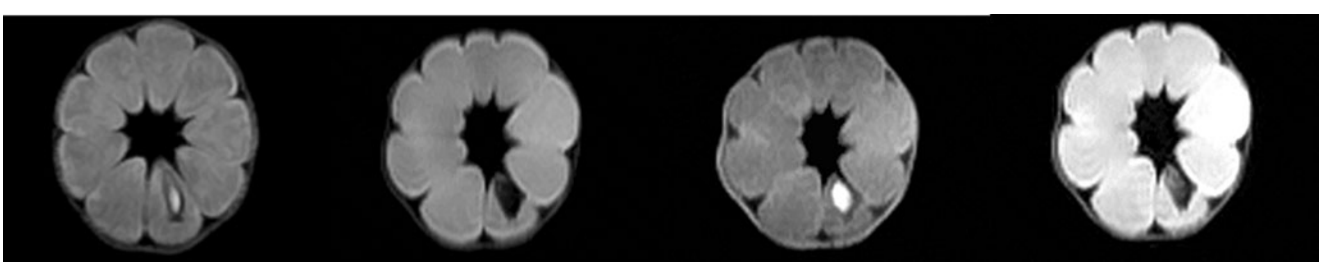

Fig. 5 Magnetic resonance (MR) images of a mandarin with one seed inside acquired using different MR sequences. *From left to right*: spin-echo TE=18 ms, TR=1,500 ms; spin-echo TE=80 ms, TR=1,500 ms; spin-echo TE=120 ms, TR=1,500 ms; gradient-echo TE=90 ms, TR=14 ms

Table 2 Summary of the internal quality of fruits and vegetables estimated using image analysis

Fruit	Imaging system	Focus on (relevant information and/or data processing methods in brackets)	References
Apple	Thermal camera	Defects (thresholding)	Baranowski et al. (2008)
	CCD camera, solid state laser diode	Texture (SSC), firmness (thresholding)	Qing et al. (2007)
	Imaging spectrograph 500–1,040 nm, solid state laser diode	Texture (skin and flesh colour), firmness SSC and TA (PCA, ANN)	Noh and Lu (2007)
	Imaging spectrograph 450–1,000 nm, tungsten halogen lamp	Defects (modified Lorentzian distribution, stepwise multi-linear regression)	Peng and Lu (2008)
	CCD camera, solid state laser diode	Texture (SSC), firmness (thresholding)	Qing et al. (2007)
Kiwifruit	3-CCD camera, laser diode emitting (785 nm)	Texture (internal)	Baranyai and Zude (2009)
Mandarin	MRI	Defects (thresholding, perimeter, second-order moment, compactness, aspect ratio	Barreiro et al. (2008)
Pears	MRI	Defects (ANOVA)	Hernandez-Sanchez et al. (2007)
Strawberry	Imaging spectrograph 400–1,100 nm	SSC, MC, pH (PLS, MLR)	ElMasry et al. (2007)
Tomato	MRI	Defects (MIA, PLS)	Milczarek et al. (2009)

system will normally separate each individual in accordance with the decision made by the computer vision system.

In order to achieve real-time operation, image processing must be very fast. For this reason, some authors have used specific hardware to minimise processing time. For instance, Aleixos et al. (2002) developed a multispectral camera capable of acquiring two images simultaneously (one sRGB image and one monochromatic NIR image) from the same scene in a citrus packing line. Image-processing algorithms were parallelised and implemented on two digital signal processors for simultaneous analysis. Fruit was graded by means of a non-linear discriminant analysis procedure that depended on colour, size and defect features. Authors demonstrated that the system was capable of correctly classifying lemons and mandarins at a rate of ten fruits per second.

Due to their enormous economic importance, many works describe real-time inspection systems for apples. Leemans and Destain (2004) presented a prototype that acquired images all over the whole surface of fruits conveyed on rollers. The rotational speed of the rollers was adjusted in such a way that a spherical object having a diameter of 72 mm made one complete rotation in exactly four images. Images were acquired at a rate of 11 images per second and camera (two cameras were used). After image segmentation, blobs were characterised by 16 features describing their colour, shape, texture and position. A hierarchical grading method was applied to classify the apples. The fruits were correctly graded with a 73% success rate, errors being mostly due to confusion between true defects and the calyx end. Bennedsen and Peterson (2005) acquired six views of each apple. A more recent work (Xiao-bo et al. 2010) describes the use of three colour cameras to inspect rotating apples and classify them into two categories (accepted or rejected) depending on the presence of defects. The three cameras work simultaneously to capture three different views of the fruit. Reese et al. (2010) used parabolic mirrors to image scenes that contained the object and its reflection in the mirrors, thus showing parts of the fruits that were hidden from the camera.

Al-Mallahi et al. (2010) developed an automatic machine vision system for sorting potatoes using UV fluorescence. The goal was to discriminate sound potatoes from undesired material (e.g. stones), and so only one image per potato was needed. They processed one image every 94 ms, and the performance of the system reached a success rate of 98%. Processed fruit and vegetables are sometimes difficult to manipulate, which makes it difficult to observe their whole surface. This is the case of satsuma mandarin segments because they are fragile and break easily. Blasco et al. (2009a) developed a machine designed to grade segments and separate them from undesired material (membranes, broken segments and segments with seeds). Segments travelled on four narrow conveyor belts under two cameras that captured the images (two conveyor belts each). A random number of segments were present in each scene, which was analysed at a rate of 48 ms/image. The vision system was capable of working at more than 20 images per second, but mechanical limitations due to difficulty in handling the segments reduced the working speed of the system to four images per second. Figure 6 shows a scheme of this machine. A similar setup was reported in Blasco et al. (2009c) for real-time inspection of pomegranate arils. In this machine, arils travelled on six narrow conveyor belts. Colour parameters were used to detect defective arils and to homogenise the sound arils in commercial colour batches. The system took only 15 ms to process each 512×384 pixel image and was capable of acquiring images from one camera while processing the image

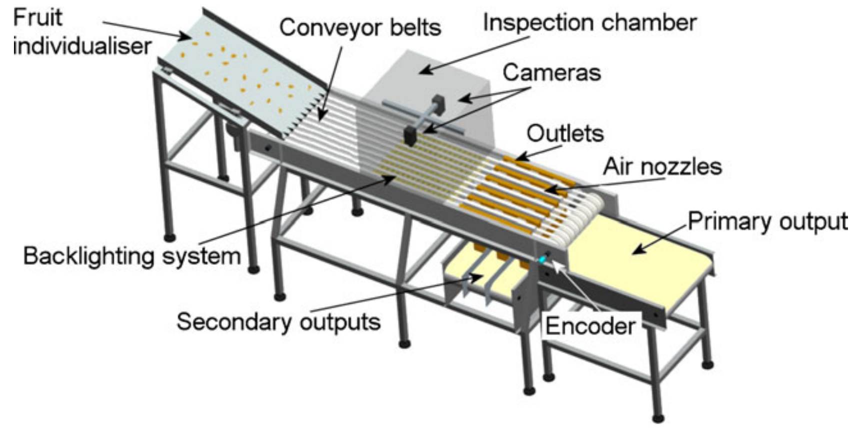

Fig. 6 Example of a machine for the automatic inspection of satsuma segments

from the other camera at the same time. Table 3 shows a summary of works on real-time processing of the quality inspection of fruits and vegetables using computer vision.

Conclusions

This paper has summarised the current state of the art on computer vision-based fruit and vegetable inspection. However, there are still challenges in this topic that have to be overcome by researchers. Some of them were identified by the CIGR Working Group on Image Analysis for Agricultural Products and Processes during their 2009 meeting in Potsdam (Germany) and are further explained below.

- *Use of new cameras*: Smart cameras or 'intelligent' cameras that incorporate image processors are now common in other research fields, and their use will

Table 3 Summary of references on real-time processing of fruits and vegetables using computer vision

Fruit	Lighting and image acquisition systems	Quality parameters (relevant information and/or data processing methods in brackets)	References
Apple	3-CCD camera, fluorescent tubes	Defects (flooding algorithm, snake algorithm)	Xiao-bo et al. (2010)
	CCD camera	Defects (thresholding, ANN, PCA)	Bennedsen and Peterson (2005)
	CDD camera	Defects (thresholding)	Bennedsen et al. (2005)
	Digital camera with interference filters, diffuse visible and NIR LED	Size (area, major and smaller diameter), defects (thresholding)	Throop et al. (2005)
	Digital camera with bandwidth filters, diffuse fluorescent tubes	Defects (thresholding, different supervised and unsupervised classifiers)	Unay and Gosselin (2006)
	2×3 CCD camera, diffuse fluorescence	Colour (RGB), shape (area, perimeter, major inertia moment, ratio of inertia moments), texture (std dev, RGB), defects (*k*-means, PCA)	Leemans and Destain (2004)
Citrus fruits	Multispectral, fluorescent tubes with polarised filters	Colour (RGB), size (average diameter), defects (Bayesian DA)	Aleixos et al. (2002)
Orange, Peach, Apple	CCD camera, fluorescent tubes with polarised filters	Colour (RGB), size (equatorial diameter), defects (Bayesian DA)	Blasco et al. (2003)
Pomegranate arils	2×RGB progressive-scan cameras, fluorescent tubes with polarising filters	Colour (R/G), defects (R/G thresholding, LDA)	Blasco et al. (2009c)
Potato tubers	UV camera, reflectance lamps		Al-Mallahi et al. (2010)
Satsuma segments	2×RGB progressive-scan cameras, fluorescent tube backlighting	Shape (LDA of circularity, roundness, compactness, area, length, symmetry, elongation and Fourier descriptors), size (major axis of inertia)	Blasco et al. (2009a)
Strawberry	CCD camera	Colour (a*), shape (*k*-means), size (horizontal diameter)	Liming and Yanchao (2010)
Sweet tamarind	CCD camera	Colour (a*), shape (*k*-means), size (horizontal diameter)	Jarimopas and Jaisin (2008)

probably become widespread in the next few years. IP cameras will also soon be included in applications for remote or web-based inspection of agricultural processes including storage of fruit and vegetables. Hyperspectral cameras are a huge source of information that is now beginning to be exploited. Three-dimensional imaging will open up the possibility of simplifying the complete inspection of objects and making the process more accurate. Moreover, UV and NIR acquisition systems are more readily available. In all these technological advances, a compromise between the increase in performance (image acquisition rate and resolution) and costs will have to be found in the coming years.

- *New imaging devices*: MR imaging is successfully employed in medicine, but it is still very expensive and slow for the massive inspection of fruits and vegetables. However, important quality information is still contained inside these products. A similar increase in use can be predicted for X-ray tomography and neutron radiography. In the case of these last two technologies, the irrational perception of possible radioactivity issues by consumers can reduce their implementation in this industry, although in many cases, it has been proved scientifically that these devices are harmless.
- *Development of more powerful image-processing techniques*: The increase in computational capacity stimulates the development of more powerful software that can be used for real-time image processing. Adaptive algorithms have yielded promising results in other fields. Computer vision-based inspection systems in agriculture must adapt to objects and circumstances that constantly change (i.e. size, colour or shape of the produce throughout the harvesting season, accumulation of dirt on camera lenses, filters and lamps). New developments in pattern recognition and massive data processing will also necessarily be included in future machine vision applications to increase the robustness and accuracy of the decisions.
- *Sensor fusion* is a set of techniques combining sensory data from distinct sources in such a way that the resulting information is more complete and accurate than that obtained when these sources are used individually. Computer vision systems, however, are not the only ones that can provide information on fruit and vegetable quality. The development of fast electronic sensors of quality attributes (electronic noses, firmness sensors, etc.), together with the advances in fusion information techniques, supply new, powerful and more robust means of automatic inspection.
- *Understanding of phenomena highlighted by the measurements*: Many current works on computer vision provide the industry with important practical solutions. However, very few of them investigate the physical–chemical and biological phenomena that are evidenced in the images. The increasing interdisciplinary nature of research groups offers the possibility of combining genetic, biological and physiological knowledge with computer vision research to take an important step towards integrated solutions for the fruit and vegetable industry. These solutions will not only allow problems to be detected but will also afford the generation of tools with which to prevent their causes.

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