Review

Sensors for product characterization and quality of specialty crops—A review

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ABSTRACT

This review covers developments in non-invasive techniques for quality analysis and inspection of specialty crops, mainly fresh fruits and vegetables, over the past decade up to the year 2010. Presented and discussed in this review are advanced sensing technologies including computer vision, spectroscopy, X-rays, magnetic resonance, mechanical contact, chemical sensing, wireless sensor networks and radio-frequency identification sensors. The current status of different sensing systems is described in the context of commercial application. The review also discusses future research needs and potentials of these sensing technologies. Emphases are placed on those technologies that have been proven effective or have shown great potential for agro-food applications. Despite significant progress in the development of non-invasive techniques for quality assessment of fruits and vegetables, the pace for adoption of these technologies by the specialty crop industry has been slow.

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1. Introduction

Fifty years ago, a new approach to characterizing fresh food materials was created, which treated food items as physical bodies to which conventional engineering concepts and methods could be applied. The aim was to maintain and enhance the quality of food products as they go through different stages of operation from harvest to postharvest handling to retailing.

Specialty crops are defined as "*fruits and vegetables, tree nuts, dried fruits and horticulture* and *nursery crops, including floriculture*" (USDA, 2004). Non-destructive (ND) testing for properties and characteristics of specialty crops is critical for monitoring and controlling product quality and safety. Sensors play the key role in identification of product properties, and thus they have been an active research area, as evidenced by thousands of engineering research publications during the past 50 years.

Quality sensing is needed or desired for most or all agricultural commodities or foods at different stages of the production/marketing chain. Specialty crops cover a wide, diverse variety of commodities, which differ greatly in morphology, composition, and physiology. Hence it is customary to classify them into different groups according to a specific criterion. *Temperate fruits*, including apple, peach, pear, citrus, and table grape, are harvested manually for fresh consumption, or mechanically for processing. *Tropical fruits* including avocado, banana, mango, and papaya are also hand harvested, while *dry (shell) fruits or nuts* are often machine harvested. We should also mention that olive and grape are two *fruit crops* of world significance; they are mainly machine harvested, where sensors are being introduced for quality monitoring. *Vegetables* contain even a much greater number of commodities; they are cultivated in different types of environments, including greenhouse. For example, there are fruit vegetables (e.g., tomato, bell pepper, zucchini) and green leafy vegetables (e.g., lettuce, spinach, cabbage, small greens). Finally, *ornamentals refer to* potted flowers, potted green plants and cut flowers.

After harvest, specialty crops may undergo all or part of these postharvest operations before being delivered to the consumer: pre-sorting, sorting, washing, refrigeration, grading (for quality classes), wrapping, and packaging (placing into cartons, small boxes, baskets, bags, nets, etc.), cold-storage (for short term, i.e., days) or controlled or modified-atmosphere storage (for long term, i.e., months). In addition, some commodities need such special treatments as ripening using gases and temperature (peaches, citrus, bananas), individual wrapping (lettuce, broccoli, cauliflower, bell peppers), cutting and small-bag wrapping (lettuce, mixed salads, fruits), or destruction (e.g., for olive oil and wine grape). Ornamental crops represent a large share of the total production for the specialty crop industry. But there is still a lack of research and progress on development of sensors for ornamental crops, except for automatic production and handling systems which have been widely adopted by the industry.

Specialty crops are living biological products that the consumer expects them to be in the best quality and safety condition. Freshness and quality, which are important to the consumer, are affected by time, handling procedure, environmental conditions, and the

processes to which they undergo. At each of these steps, the freshness and quality of specialty crop products need to be monitored and controlled. Traditional manual expertise for quality inspection is no longer adequate nowadays, and only sensors can provide solutions for monitoring and controlling the quality of specialty crops.

A number of reviews on non-invasive, fast technologies for fruit and vegetables quality sensing have been published (Chen and Sun, 1991; Abbott et al., 1997; Studman, 2001; Butz et al., 2005). Many of these review papers covered a broad range of sensing techniques, with a selected few that also discussed the feasibility of these techniques for industrial applications (Abbott, 2004; Walsh, 2005). Moreover, several recent reviews are focused on selected techniques, such as mechanical methods for firmness measurement (García-Ramos et al., 2005), size characterization techniques (Moreda et al., 2009), computer vision (Brosnan and Sun, 2002; Du and Sun, 2006), near-infrared (NIR) spectroscopy (Nicolai et al., 2007), nuclear magnetic resonance (NMR) (Aristizábal, 2007), biosensing (Mello and Kubota, 2002; Patel, 2002), wireless sensing (Ruiz-Garcia et al., 2009), and plant diseases detection (Sankaran et al., 2010). The needs for this area of research are mainly driven by the specialty crop industries to meet increasing consumer demand for better quality and safer fresh products.

A large number of recent publications on non-destructive detection of food quality are related to the utilization of electromagnetic radiation in a wide range of frequencies. Electromagnetic radiation-based technologies have shown great potential; some of them have been successfully used for monitoring the quality of specialty crops. Successful application of these technologies requires the combination of effective sensors with sophisticated mathematical models and computer algorithms to establish relationships between selected physical/chemical properties and quality attributes of the product. As a result, a large number of papers published recently are focused on utilizing different non-destructive (ND) optical techniques for quality detection of agro-food products. Great advances have been made in spectroscopy and computer vision, and these techniques are being widely used for quality inspection and control of products in many industries including food. As technologies based on VIS, NIR, mid-infrared (MIR), and ultra-violet (UV) are becoming more affordable and equipped with more user-friendly data treatment and calibration capabilities, they have fostered further development of detection procedures for different quality- and composition-related properties of fruits and vegetables.

Over the past 10 years, a number of new technologies based on electromagnetic properties have emerged, whereas great progress has also been made on other existing technologies. They include X-ray, nuclear magnetic resonance (NMR) or magnetic resonant imaging (MRI), fluorescence, and with less success until now, electrical impedance and permittivity (mainly microwave), thermal sensing and selective gas/volatile sensing. These developments have opened new areas of research as well as new applications for sensing quality of specialty crops.

This review covers different sensing techniques, with emphasis on those emerging technologies like NMR, MRI, wireless sensor networks (WSN) and radio-frequency identification (RFID), for fruits and vegetables and their potential for industrial applications.

2. Computer vision for internal quality

Numerous review articles have been published on computer vision technology for quality inspection of food and agricultural products (Chen et al., 2002; Brosnan and Sun, 2004; Aguilera and Briones, 2005) and horticultural products in particular (Abbott, 2004; Butz et al., 2005; Nicolai et al., 2007). This section provides a brief review of selected vision technologies, especially those emerging technologies that are showing great promise for assessing internal quality of horticultural products, i.e., sensory attributes (texture and flavor), nutritive values, chemical constituents, functional properties and internal defects or physiological disorders.

2.1. Visible/near-infrared

The reflectance properties of a product in the visible region (approximately 400–780 nm) are perceived by humans as color, which provide pigment information about commodities. Skin color has been considered indicative of maturity for some horticultural products such as banana, mango, and tomato (Edan et al., 1997). Color, in the human perception directly relates to product appearance (Abbott, 1999), and the relationship of pigments, and therefore the VIS reflectance fingerprint, with deterioration and evolution of fruits during ripening has been established. Many constituents of fruit quality, including those that contribute to taste and aroma as well as antioxidant potential are synthesized in chloroplasts or chromoplasts, and in the genes (Barry, 2009). In the food industry, quality factors are often linked to product pigments or color features. VIS imaging sensors are thus effective techniques for quality detection of fruits, especially for maturity and ripeness. Similar results have been established in green plants.

Broadband images (i.e., gray-scale and color images) are inappropriate for detecting specific quality attributes (other than color attributes or certain surface blemishes that are visible) because many chemical components (pigments, sugar, starch, water, protein, etc.) are sensitive to specific narrow wavebands in or beyond the visible region. Hence spectral imaging technology, which acquires single or multiple images at selected wavelengths, is used for detection of specific quality attributes of horticultural products. Spectral imaging may be categorized into multispectral and hyperspectral. Multispectral imaging acquires spectral images at a few discrete narrow wavebands (the bandwidth may range between 5 and 50 nm). Hyperspectral imaging, on the other hand, acquires tens or hundreds of spectral images at congruous wavelengths or wavebands over a specific spectral region.

Multispectral imaging has been used to detect quality-related chemical components, such as fruit pigment concentration, and distribution of sugar (or soluble solids) in fruits (Peng and Lu, 2007). Since color measurements usually give poor results for ripeness assessment and defect detection, NIR multispectral imaging technology has been developed and is now commercially available for fruit blemish detection. The technology can achieve up to 90% accuracy in detecting damaged fruits with visible blemishes of greater than 5 mm in diameter. Research also showed that multispectral scattering images can be used to evaluate the firmness of fruits (Peng and Lu, 2007; Qing et al., 2007). The technique uses either a regular digital camera or a multispectral imaging device to capture spectral scattering images from the surface of a fruit generated by a focused light beam (either monochromatic such as laser or polychromatic) at single or multiple wavebands. Since scattering profiles are influenced by density, cell structures and chemical composition of the fruit, they can be related to fruit firmness and/or soluble solids content. Spectral scattering prediction of fruit firmness showed good correlation ($r \sim 0.90$) with Magness–Taylor firmness measurement, the standard destructive penetration test (Peng and Lu, 2007; Qing et al., 2007). The technique is noncontact,

fast and relatively easy to implement; moreover, it could be used for simultaneous assessment of fruit firmness and soluble solids content. However, the technique, like NIR spectroscopy which captures spectral information, relies on calibration models to predict fruit firmness and/or soluble solids content. In addition, fruit shape and size need to be considered for better characterization of spectral scattering features.

Hyperspectral imaging integrates the main features of imaging and spectroscopy to acquire both spectral and spatial information from the product simultaneously, thus making it especially suitable and much more powerful for inspecting horticultural and food products, whose properties and characteristics often vary spatially (Kim et al., 2001; Gowen et al., 2007). Hyperspectral imaging is commonly implemented in one of the two sensing modes: push-broom or line scanning mode and filter-based imaging mode (Lu and Chen, 1998). In-line scanning mode, the imaging system line scans the moving product items, from which three-dimensional (3D) hyperspectral images, also called hypercubes, are created. In filter-based imaging mode, spectral images are acquired from the stationary product items for a sequence of wavebands using either liquid crystal tunable filter (LCTF) or acousto-optic tunable filter (AOTF). Line scanning mode is most commonly used because it is relatively easy to implement, especially when real-time, online applications are needed. Filter-based hyperspectral imaging systems require more complicated calibration and are not suitable for online applications. A hyperspectral imaging system needs a high performance digital camera covering the spectral region of interest and having a large dynamic range (12-bit or higher is preferred), low noise level (with a cooling device to reduce the sensor's thermal noise), and good quantum efficiency. Moreover, an imaging spectrograph, which disperses line images into different wavelengths, is an essential component for a line scanning hyperspectral imaging system; it should have an appropriate optical resolution and spectral response efficiency with minimal aberrations. In addition, it is critical to have an appropriate DC-regulated light source that is highly stable, with smooth spectral response. Those who have sufficient knowledge and experience in optics and imaging may use off-shelf optical components to assemble a hyperspectral imaging system to achieve cost savings and meet their specific application needs in the laboratory. However, most users would be better off by purchasing a turn-key hyperspectral imaging unit from a commercial company (e.g., Headwall Photonics Inc. and Themis Vision Systems in U.S. and Specim in Finland).

Hyperspectral imaging technology was used for measuring fruit maturity, firmness and soluble solids content (ElMasry et al., 2007; Lu and Peng, 2007; Noh et al., 2007), and for detecting bruises and bitter pits on apple and mushroom (Nicolaï et al., 2006; Gowen et al., 2008) deterioration in mushroom (Taghizadeh et al., 2010) and chilling injury and internal defect of cucumber (Cheng et al., 2004; Ariana and Lu, 2010). A spatially resolved technique based on hyperspectral imaging was developed for measuring the spectral absorption and scattering properties of horticultural and food products (Qin and Lu, 2008). Because of its ability to acquire a large amount of spatial and spectral information, hyperspectral imaging will find more and more applications in quality and also safety inspection of horticultural and food products in the coming decade. However, two major issues need to be addressed in application of the technology. First, hyperspectral imaging acquires spectral images at contiguous wavelengths and considerable redundancy exists in the hyperspectral image data. Therefore an effective algorithm is needed to reduce the data dimensionality and identify most useful features with fewer wavebands. While many generic application algorithms have been developed for this purpose, it is important that the users choose an appropriate one that would meet their application needs. Second, up to now, speed and time needed to acquire and process a huge amount of image data has

been the impediment to real-time, online application of the technology. However, as the sensor and computer technologies are evolving rapidly, it is now feasible to implement hyperspectral imaging technology for fast, online sorting and grading of horticultural and food products (Chao et al., 2008; Ariana and Lu, 2010; Herrero-Langreo, 2010). This opens a new horizon for effective applications of the technology for inspection of different quality factors of horticultural products. The expected accuracy in dedicated applications (of what???) is, based on present experiments, 80–90% correct classifications at least. Hyperspectral imaging can be adapted and/or simplified to the use of indexes based on a small number of wavelengths, thus improving industrial feasibility.

2.2. Fluorescence spectroscopy

Fluorescence spectroscopy measures the light of longer wavelengths emitted from the object after it is excited with a beam of light of short wavelengths (usually in the ultra-violet region). For the last 20 years, laser-induced fluorescence has been used for vegetative studies, such as to monitor stress levels and physiological states in plants (Belasque et al., 2008). Two types of fluorescence: (i) blue-green fluorescence in about 400–600 nm range, and (ii) chlorophyll fluorescence in about 650–800 nm range, are produced by green leaves. Fluorescence spectroscopy has been used to monitor nutrient deficiencies, stress and diseases in plants, in laboratory or field conditions. Application of this technology to industrial processes is yet to be fully developed.

2.3. X-rays

X-rays cover the spectral range of 0.01–10 nm, which falls between gamma rays and ultra-violet rays. X-rays can penetrate through most horticultural products and the level of X-ray energy transmitted through the product depends on the incident energy and absorption coefficient, density and thickness of the product. X-ray imaging is thus useful for evaluating quality/maturity and internal defect of horticultural products. Various X-ray imaging technologies are available; they include X-ray radiography which scans layers of the product to create two-dimensional (2D) images and computed tomography or CT scanning which creates 3D images. X-ray imaging showed potential for evaluating the maturity of peach, mango, and lettuce (Brecht et al., 1991; Barcelon et al., 1999a,b). Physiological disorder in the plant tissues and the presence of insects or foreign objects often cause changes in the density and water content of the product. Hence, X-ray imaging is particularly useful for detecting various types of internal defects or foreign objects in horticultural products such as watercore and internal browning in apple, translucence in pineapple, freeze damage and dry sections in orange and tangerine, pits or pit fragments in tart cherry and peach, and the presence of insects in fruit (Tollner et al., 1992; Peiris et al., 1998; Shahin et al., 1999; Lammertyn et al., 2003a,b; Velasco and Medina, 2004; Hansen et al., 2005; Haff et al., 2006).

2.4. Other vision technologies

Several emerging vision technologies such as near-infrared (NIR) tomography and terahertz imaging have recently received considerable attention in medical diagnosis and non-destructive evaluation of non-food products (Gibson et al., 2005; Pickwell and Wallace, 2006; Kemsley et al., 2008). NIR tomography provides images for the interior of an object. As NIR light (usually in the range of 750–1300 nm) is injected into a turbid biological object, its attenuation and scattering is tracked by multiple sensors positioned at different locations from the incident point, and 2D or 3D images are constructed by using inverse algorithms to solve an appropriate diffusion theory model. However, since light scattering is dominant in the region of 700–1300 nm, it presents considerable technological challenges in obtaining high resolution images.

Terahertz imaging technology represents another new frontier for non-destructive evaluation of food and biological materials (Pickwell and Wallace, 2006). Terahertz radiation refers to the spectral region of 0.1–3 mm, falling between the far infrared and microwaves. Terahertz rays correspond to the energy level of molecular rotations and vibrations of DNA and protein, and hence they may provide spectral fingerprints for biological tissues. Terahertz wavelengths are sensitive to water and the technique can thus be useful for assessing tissue condition. The technology is still in an early development stage, but it could present some interesting opportunities in quality evaluation of horticultural products.

Thermal imaging (TI) is another emerging technique for non-invasive analysis in the food industry. Recent advances and potential applications for TI for food safety and quality have been reviewed (Gowen et al., 2010). Temperature mapping, measuring infrared radiation (long wave greater than 8 μm) emitted by the body surface, where temporal and spatial distribution patterns are obtained, shows potential for food product quality and safety monitoring. While applications are reported for apple, tomato (detection of bruises), potato (freezing damage) and citrus (drying time), the technology is still in experimental stage.

3. Nuclear magnetic resonance (NMR) spectroscopy and imaging

Since the discovery of the magnetic resonance phenomenon in 1946 and subsequent achievements, nuclear magnetic resonance (NMR) has become one of the most significant non-invasive techniques for internal inspection of biological objects (see Table 1). Derived from NMR are NMR spectroscopy, NMR relaxometry and magnetic resonance imaging (MRI). For NMR spectroscopy resonance frequency encodes the chemically equivalent nuclei populations at different electronic and chemical environments so that the outcome is an NMR spectrum where intensity is plotted versus frequency. MRI devoted spatial codification of the signal intensity produces a two- or three-dimensional image. NMR relaxometry identifies nuclei populations distinguishable due to the different signal decay time constants, that is, relaxation times. NMR technique offers information about the inside of an object, thus making it feasible for quality classification of fruits and vegetables. NMR is a useful non-destructive monitoring technique for a wide range of applications because it is sensitive to the concentration, chemical environment, mobility, and diffusion among other phenomena, related to certain nuclei. These phenomena are influenced by cell compartmentation and tissue microstructure so that the NMR signal also acts as sensor of the tissue integrity. A number of review articles and books on applications of NMR for quality evaluation of fruits and vegetables have been published recently (Hills and Clark, 2003; Aristizábal, 2007; Hernández-Sánchez et al., 2009). The first reported applications focused on quantification of main components such as water and fat content by NMR spectroscopy. Subsequent studies performed more complex analysis based on NMR relaxometry. MR images allow internal tomography where tissue contrast mainly arises from differences in relaxation times and proton density, and are also used for characterization.

3.1. Stationary examination

Studies that have been conducted in fruits and vegetables with NMR techniques mainly relate to the maturity and ripeness, internal damage and defect, and physiological disorders appearing during storage and caused by pre- and postharvest conditions (Hills

Table 1
Summary of quality attributes and disorders in fruits and vegetables studied by NMR relaxometry (MRR), NMR spectroscopy (MRS) and MRI techniques (including proton density (PD) maps).

Product	Maturity/sugar content	Bruises/voids/seeds	Tissue breakdown	Heat injury	Chill/freeze injury	Infections
Fruit						
Apple	MRR/MRI	MRI	MRI/MRR PD maps			
Avocado	MRS/MRI					
Banana	MRR					
Cherimoya	MRR/MRI					
Durian	MRS/MRI		MRI			
Kiwifruit	MRR				MRI/MRR	MRI
Mandarin	MRR PD maps	MRI				
Mango	MRS/MRR			MRI		MRI
Mangosteen	MRI					MRI
Melon	MRS	MRI	MRI			
Nectarine			MRI			MRR PD maps
Orange	MRS/MRR	MRI			MRI	
Papaya				MRR		
Peach		MRI			MRR/MRI	
Pear		MRI	MRR/MRI			
Persimmon					MRI	
Pineapple	MRR/MRI					
Tangerine	MRI	MRI	MRI			
Watermelon	MRS	MRI				
Berries						
Blueberry	MRI				MRI	
Grape	MRS/MRR					
Strawberry						MRI
Small, stone fruits (drupes)						
Cherry	MRR/MRS	MRI				
Olive	MRI	MRI				
Plum/prunes	MRS					
Vegetables						
Courgette/Zucchini					MRI	
Cucumber					MRI	MRI
Onion		MRI				
Potato	MRR/MRI	MRI	MRI			MRI
Tomato	MRR/MRI					

and Clark, 2003; Aristizábal, 2007). NMR spectroscopy and MRI are used to monitor air spaces shrinkage and NMR relaxometry are recently reported to detect decreasing relaxation times with ripeness (Musse et al., 2009). T_2 times and relaxation times were used to estimate tomato firmness with negative results (Tu et al., 2007), and the ripening of kiwi (Hills and Clark, 2003), banana (Raffo et al., 2005) and cherimoya (Goni et al., 2007). In persimmon T_1 declined abruptly during ripening whereas T_2 increased smoothly (Clark and MacFall, 2003). Further positive results are published on apple and on pear related to sugar content and firmness, both based on analysis of T_2-weigthed MR images (Hills and Clark, 2003; Aristizábal, 2007). Water suppression by diffusive attenuation was used in T_1 measurements to successfully measure Brix in intact cellular tissue of apple and strawberry (Marigheto et al., 2006), and oil content in avocado (Marigheto et al., 2005), and many other products (Aristizábal, 2007), which should be useful for rapid, online measurements.

Among different types of internal defect, insect damage, fungal infection, bruise, and the presence of seeds or pits have been major issues. Larvae cavities were observed in MR images for pear, mango and peach (Aristizábal, 2007). Fungus infection has been inspected using MRI in nectarine, strawberry, grape, mandarin, orange and coconut (Hills and Clark, 2003; Aristizábal, 2007). MRI has also provided contrasted images for the inspection of bruises in apples, peaches, pears, onions, strawberry guava and potato (Aristizábal, 2007). Multivariate image analysis of MR images of tomato proved to be effective for predicting the conductivity score of pericarp tissue in tomatoes for bruises detection (Milczarek et al., 2009). The presence of seeds or pits was inspected with MRI in a number of products such as plum, cucumber, peach and olive, cherry, mandarin and orange (Kim et al., 2008; Hernández-Sánchez et al., 2009). For cherries and olives one-dimensional MR images (projections)

sufficed (Hills and Clark, 2003) due to the large proportion of volume occupied by the pit within the fruit whereas for the other products two-dimensional MR images were required for detection in order to avoid partial volume effect (Hernández-Sánchez, 2006).

Physiological disorders have also been of great interest. Among those developed during the pre-harvest period works have mainly focused on freezing damage and watercore. Aristizábal (2007) cited an early work where dehydrated vesicles were detected in MR images of oranges affected by freezing damage. Early works showed the viability of detecting freezing injuries in products such as blueberries, kiwifruit, persimmons and peaches by means of contrast changes in MR images, and in apple tissue through MR relaxometry (reviewed by Hills and Clark, 2003). Damaged areas present a reduction of the proton density and the relaxation constant T_2 (Gambhir et al., 2005), which are the source of the contrast in the MR images. The percentage of damaged tissue was addressed in static and dynamic MR images obtained from oranges on the tree that had been exposed at freezing temperatures (Hernandez-Sanchez et al., 2004). Dehydrated tissue and cavities were also observed by Aristizabal Torres (2006) in similar samples. Fast detection of seeds and freeze damage in mandarine citrus fruit was performed using MRI in a 1 T industrial grade permanent magnet (Kim et al., 2008). Detection of watercore in apples was feasible because the reduction of the proton density and the relaxation times in affected tissue involve intensity contrast in the MR images (Hills and Clark, 2003; Marigheto et al., 2005). The postharvest disorders appearing during storage that have been thoroughly inspected with NMR techniques are internal browning and internal breakdown, mealiness and wolliness, core breakdown in apples, peaches and pears (Lammertyn et al., 2003c; Hernandez-Sanchez et al., 2007; Cho et al., 2008; Marigheto et al., 2008).

Most of the aforementioned works have been undertaken with commercial NMR equipment designed for medical purposes. Such equipment operate at high magnetic field strength of more than 2 T with high performance and expensive hardware requiring high initial capital investments. In addition, they are difficult to implement in an industrial environment. Hills and Clark (2003) and Hills (2006) suggested that the field homogeneity within large volumes in low-field equipment and the compatibility with commercial fruit graders should be major subjects for advancing the technology into industrial applications.

3.2. Moving measurements

Industrial implementation of NMR techniques for internal inspection requires satisfactory performance under motion conditions. This issue has been studied in recent works (Hills and Wright, 2006).

For pit detection in cherries and olives, MR projections were acquired with a 2 T NMR spectrometer (reviewed by Hills and Clark, 2003) while samples were conveyed at belt speeds ranging from 0 up to 250 mm/s. Classification errors were greatly affected by sample orientation. In detecting maturity in avocados (reviewed by Hills and Clark, 2003) MR spectra were analyzed. The conveyor speed varied from 0 to 250 mm/s and the fruit were placed at different orientations with respect to the radio-frequency coil. The researchers found high correlation with dry weight (from 0.894 to 0.975) as the motion of the sample had small effect on the acquired signal when single-shot sequences are used. A real-time, in-line NMR quality evaluation sensor was designed, constructed and tested for several fruits to acquire NMR signals when a sample is within ±50 mm of the NMR coil center at speeds ranging from 0 to 300 mm/s (Kim and McCarthy, 2006). Detection of freeze injury in citrus under motion conditions (Hernandez-Sanchez et al., 2004) was evaluated using an NMR spectrometer of 4.7 T. Fast Low Angle Shot (FLASH) images were obtained as oranges were conveyed at 50, and 100 mm/s belt speeds. Image blurring was induced by the excitation of consecutive slices driven by the axial location of the field of view (FOV). For seed identification in citrus (Hernandez-Sanchez et al., 2006) the re-orientation of the FOV from axial to coronal images solved the problem of signal superimposition, and necessitated the development of devoted algorithms to correct phase shift induced by sample motion. The features extracted automatically from the motion-corrected images were not significantly different from those extracted from the static ones. FLASH images and combined spiral radial (COMSPIRA) images were obtained from seedless and seed-containing mandarins while conveyed at 50 mm/s. Phase shift correction was applied for image reconstruction prior to image analysis. The seed identification was up to 100% accuracy using COMSPIRA images and image postprocessing based on the variance of 2D histograms (Barreiro et al., 2008). Results have yet to be validated at low-magnetic field strengths and higher conveyor speeds. A 1 T industrial grade permanent magnet was used to acquire MR images in mandarines and threshold-based image analysis has proven successful in detecting seeds and quantifying freeze damage (Kim et al., 2008). For inspection of internal breakdown in pears coronal FLASH images were acquired from the equatorial slice of pears conveyed at about 50 mm/s through a 4.7 T magnet (Hernandez-Sanchez et al., 2007). Correct classification was 98.4% although the final performance remains to be validated at low-magnetic field strengths and higher conveyor speeds. Internal browning in apples was inspected with a low-cost, low-field instrument of 0.13 T (Chayaprasert and Stroshine, 2005) obtaining T_2 global measurements at different belt speeds up to 250 mm/s. Encouraging results were obtained at 50 mm/s with a classification error of 12% although performance decreased at higher speeds.

To date, none of these technologies have been implemented in the industry. Hernández-Sánchez et al. (2009) state that such technology transfer would require closer and more active interactions between researchers and the food industry, in order to develop reliable and cost-effective NMR equipment with the capacity to meet industrial application needs.

4. Computer vision for external quality and defects

Kader (2001) classified the quality attributes of fresh horticultural produce in four groups: appearance, texture, flavor, and nutritional factors. Appearance traits include size or dimension, shape, surface texture, surface color, and external or surface defects. Appearance factors define external quality and directly influence consumers in purchasing a product, and they can be evaluated by means of computer vision techniques. For some authors (Brosnan and Sun, 2004) the terms *computer vision* and *machine vision* are synonymous, whereas for others (Graves and Batchelor, 2003) *computer vision* is a science. Computer vision systems measure the reflectance of an object but also the distance (range) to the object. While reflectance data are only necessary for color assessment and external defects identification and quantification, size, shape and surface texture can be evaluated either from reflectance or from range data.

As in human vision, computer vision is highly dependent on by the level and quality of illumination, regarding spectrum, stability and spacial distribution. Two key parameters in any computer vision system are spatial resolution and dynamic range. Resolution is the ability to spatially resolve details in an image, while dynamic range refers to the range of light levels that can be captured by the imaging device. The image sensors used in computer vision are based on solid state charge-coupled device (CCD) or complementary metal-oxide semiconductor (CMOS) technology. There are also some applications using vidicon tubes and charge injection device (CID). CID sensors are the preferred option when high reflections are an issue, because CCDs are easy to saturate under these conditions. An alternative way to overcome when specular reflection, while sensing with a CCD, is to use polarizing filters. Both CCD and CMOS sensors are available in area-scan, line-scan version. Most cameras used in commercial fruit sorting systems are equipped with area-scan sensors, also known as matrix or array sensors.

4.1. Size and shape

Although computer vision-based determination of axes or diameters, projected area and circumference is considered a solved issue, accurate fruit volume measurement at high speed has only become available in the last few years (Moreda et al., 2009). Accurate volume determination is of interest for online electronic density sorting. Fruit density sorting is useful because there are products like grapes or kiwifruit whose density is correlated to compositions such as soluble solids (Sugiura et al., 2001; Jordan and Clark, 2004). Furthermore, density determination is of interest for separating freeze-damaged citrus fruits (Miller et al., 2006), puffy tangerines (Aleixos, 1999), fruits with internal damage caused by insects (Forbes and Tattersfield, 1999), watermelons with a high degree of hollowness (Kato, 1997), and apples with watercore. The typical accuracy of 1 mm offered by machine vision equipment manufacturers suffices for the sizing of most fruits and vegetables based on fruit axes or diameters. However, commercial vision systems that compute volume from 2D images generally do not yield high precision volume measurements required for density sorting. Nowadays, 3D machine vision systems are being introduced in some food industries (Montrose Technologies; SICK-AG, 2010), and this trend could be further expanded into the fresh produce industry, where 3D cameras could be used, besides for

accurate volume measurement, for shape sorting and surface area quantification.

Fruit shape is one of the most important factors for classifying and grading fresh horticultural produce, but in many packinghouses fruit shape is still manually determined (Xiaobo et al., 2008). Fruit shape determination is of interest for several commercial reasons, including elimination of ill-shaped fruits and fruit damages which are located on non-flat fruit surfaces (Hryniewicz et al., 2005). Moreover, misshapen fruits such as pear-shaped grapefruit are often considered defective (Syvertsen et al., 2005). For some commodities like banana, mango, broccoli or cauliflower, shape is used as a maturity index (Studman, 2001).

Automated shape determination techniques can be classified into two categories: 2D and 3D. Two-dimensional methods analyze the shape of a planar digital image of the object taken by a video camera, whereas 3D approaches try to reconstruct the object's 3D surface. Few works have dealt with online 3D shape inspection for specialty crops, and most of the research reported so far has relied on digital planar images. Noordam (2010) used six laser-cameras to construct the 3D shape of sweet pepper fruits, based on triangulation. Two-dimensional shape features can be measured independently or by combination of size measurements (Du and Sun, 2004). Circularity, aspect ratio and compactness are examples of simple mathematical combinations of size measurements. More sophisticated shape analyses can be performed independent of size measurements; these can be classified (Zhang and Lu, 2004) into region-based (Heinemann et al., 1995) and contour-based (Abdullah et al., 2006; Menesatti et al., 2008; Jarimopas and Jaisin, 2008; Riyadi et al., 2008; Costa et al., 2009). Table 2 summarizes classification accuracies reported by several researchers using different shape description techniques. Among size-independent shape analysis techniques, contour-based techniques are generally more popular than region-based approaches. Region-based methods are more robust as they use all the shape information available. It should be mentioned that although high classification accuracies have been reported (Table 1), most of the works were undertaken off-line and/or under laboratory conditions.

The potential of imaging sensors for quality classification of potted plants under greenhouse production has been explored recently. Commercial protected glasshouse crop environments allow many important environmental factors (e.g., lighting and temperature) to be partly or totally controlled during growth (Parsons et al., 2009). It is, however, difficult to assess ornamental quality because only subjective references can be used. Feed-forward artificial neural networks were used to segment top and side view images of three contrasting species of bedding plants. The segmented images provided objective measurements of leaf and flower cover, color, uniformity and leaf canopy height. The extracted image features would explain 88.5%, 81.7% and 70.4% of the panel quality score. Prediction models based on artificial neural networks cannot achieve high accuracy, and most of them have poor capabilities for systematic improvement and low robustness.

4.2. Surface texture

Surface texture refers to the topographic or relief features on the outermost boundary of an agricultural product. Typical examples include the wrinkles on prunes and raisins and the rough or pebbly surface of an orange. Surface texture is a quality parameter in many fruits. For example, high quality raisins are categorized by fine wrinkles. Fekete and Olasz (2005) monitored the senescence of apples kept in a cold room by analyzing fruit surface wrinkles. In some commodities, maturity is partly defined by surface texture. Surface texture is difficult to measure, because it is a true 3D measurement. Triangulation laser range finding, often abbreviated as 'laser scanning' (although 'laser scanning' is misleading, since it

Table 2
Summary of features for different research works aimed at describing product shape.

Shape description technique	No. of dimen-sions	Commodity	Classification accuracy (%), no. classes	Classification technique	Reference
Discrete wavelet transform	2D	Papaya	98, 2	LDA[a]	Riyadi et al. (2008)
Fourier descriptors	2D	Pear (cv. *Huanghua*)[b]	90, 4	ANN[c]	Ying et al. (2003)
Fourier descriptors	2D	Hazelnut	96.3, 2	PLSDA[d]	Menesatti et al. (2008)
Fourier descriptors	2D	Starfruit	100, 3	Threshold based on 4th, 5th and 6th order harmonics	Abdullah et al. (2006)
Shape signature	2D	Sweet tamarind	96, 3	Index value	Jarimopas and Jaisin (2008)
Area moments	2D	Apple	92.3, 2	Threshold based on 3rd order moments	Heinemann et al. (1995)
Combination of size features	2D	Bell pepper	96, 2	ANN	Okayama et al. (2006)
Combination of size features	2D	Strawberry	98.6, 3	Parameter value (threshold)	Bato et al. (2000)
Laser scanning	3D	Strawberry	90, vna[e]	ANN	Katayama et al. (2003)
Artificial retina based on CSM[f]	3D	Orange and aubergine (eggplant)	96, 2 and 92, 2, respectively	ANN	Kanali et al. (1998)

[a] Linear discriminant analysis.
[b] *Huanghua* pears are hardly pyriform; they look more like apples.
[c] Artificial neural network.
[d] Partial least squares discriminant analysis.
[e] Value not available.
[f] Charge-simulation method.

also accounts for *time-of-flight* laser range finding), is a well-known method used to measure surface features of manufactured goods, which could be used in fruit surface texture analysis. A more popular approach for produce surface texture inspection is the use of 2D computer vision. Dunn (2007) developed image analysis algorithms to classify citrus fruits according to peel roughness by analyzing planar images. The experimental setup consisted of a source of light, the fruit (orange) and a video camera, arranged horizontally at the vertices of a right-angled triangle, so that the image acquired by the camera was a sort of 'half-moon'. With this setup, the ragged 'terminator' line separating the lit and shadow zones of the orange surface was frequency and amplitude analyzed. In this concept, if the object is a billiard ball instead of a citrus fruit, the 'terminator' line would be straight instead of ragged. A strong correlation between the computer vision measurements and the subjective visual rankings was reported, but the results were not quantified or validated.

Other potential techniques for surface texture analysis are stereovision, moiré interferometry, holographic interferometry, and Fresnel diffraction. Holographic interferometry allows very high spatial discrimination in the order of 10^{-10} m, but the technique currently is too expensive to be practical for specialty crops.

4.3. Surface color

Color is a human perception by definition, which has long been used in the assessment of fruit quality. In fruits, a decrease in chlorophyll content of the skin is correlated with increasing maturity; this is traditionally used as the criterion for visual assessment of fruit maturity (Crisosto et al., 2007). Some fruits have one color homogeneously distributed on the skin surface, and the averaged surface color is a good quality indicator for these fruits. In the early years of application of computer vision to fruit inspection, fruit color assessment relied on grey-scale images captured by monochrome cameras, for instance, for classification of bell pepper or oranges in color classes. This approach is only applicable when the product is mono-colored, and defect detection is not required. Other fruits, like some cultivars of peaches and apples, have a secondary color that is frequently used as an indicator of maturity, which often is not reliable.

Produce color sorting in modern packinghouses is performed using RGB color video-cameras. Each pixel in a color image consists of three intensity values, since any color can be reproduced by the combination of three primary color components: blue, green, and red. Each of these components: R, G and B, covers a large part of the visible spectrum, as compared to multispectral cameras that use narrow bands. The techniques require previous and also continuous training to adapt the system to the great color variability present in products like fruits (Blasco et al., 2007; Lleo et al., 2009). In general, online fruit color grading by means of computer vision is considered solved and is widely used now by the industry. However, color sorting is not suitable for measuring or assessing internal quality, which may require multi- and hyperspectral imaging as discussed above.

Image color accuracy and spatial resolution have been greatly improved in three-chip (CCD, CMOS) cameras (Pitre et al., 2010). Three-chip color cameras use dichroic prisms to direct the light in each of the three wavebands. Single-chip color cameras, with substantially increased resolution without diminishing sensor sensitivity and dynamic range, were recently developed (Digital-Photography-Review, 2008).

4.4. External or surface defects

Blemish sorting has been addressed together with color sorting for many years mainly because many defects exhibit special color characteristics. For instance, apple skin affected with rus-

seting is brown, and severe fungal attacks in orange are shown as a greenish or whitish peel. In fact, human inspectors in packinghouses depend heavily on color to differentiate defects. Xing et al. (2007) stated that although computer vision systems have received much attention for sorting apples, oranges, peaches and other fruits into different categories according to size and color, they still have some limitations in surface defect detection. Blemishes are difficult to detect when their color coincides with the color of the sound peel. Recent techniques use multispectral (Aleixos et al., 2002), or hyperspectral imaging (Tallada et al., 2006; Kim et al., 2007) to detect blemishes. Guyer and Yang (2000) used artificial neural networks and spectral imaging for identification and quantification of different types of cherry surface defects, like dry crack, wet crack, mold, and bruise. An average of 73% classification accuracy was achieved for correct identification as well as for quantification of different types of cherry defects. No false positives or false negatives occurred; errors resulted only from misclassification of different types of blemishes or the quantification of the size or number of defect. Tallada et al. (2006) took spectral images from strawberries in the range from 650 to 1000 nm at 5 nm intervals to determine two optimal wavebands for the detection of bruises. Optimal wavebands of 825 nm and 980 nm were obtained using stepwise linear discriminant analysis. The non-bruised samples were perfectly classified as non-bruised, i.e., there was no false-positive classification. Bruised samples with larger damage (applied in the laboratory) were perfectly classified, while variations in the accuracies for small bruises were observed, and they depended on degree of ripeness. Kim et al. (2007), using a NIR two-band reflectance ratio coupled with a simple classification method based on the mean intensity and homogeneity of the ratio, achieved a 99.5% apple defect classification.

The detection of skin defects is closely related to the ability to correctly identify the stem cavity or the calyx. The 'stem/calyx issue' has been tackled through different approaches: mechanical orientation, 2D image processing, 3D shape capturing, and logical comparison of images corresponding to different wavelengths, and is already present in commercial fruit handling equipment. Throop et al. (2005) described a handling system that oriented several apple cultivars with a success rate higher than 97.6%. When the 3D shape of the fruit is reconstructed, the problem of mistaking the stem cavity for a blemish disappears. Yang (1996) recovered the 3D shape of apples by projecting structured light on the fruit surface, the *shape-from-shading* technique to construct the 3D surface of apples from 2D NIR images; they report a 90.1% defect detection at a throughput of 1 fruit per second. Wen and Tao (2000) used a dual-camera system comprised of a visible-NIR camera and a mid-infrared (MIR) camera. The NIR camera detected both defects and concavities, whereas the MIR camera detected only concavities. Defect detection was achieved by logical comparison of the images delivered by the two cameras. Finally, the above-mentioned NIR processing regime of the work by Kim et al. (2007) overcame the presence of stem/calyx on apples. More recently, 3D reconstruction using a shape-from-shading approach was combined with a quadratic facet model to reconstruct the 3D concave shape (Jiang et al., 2009).

5. NIR and IR spectroscopy

Different NIR and IR spectroscopic techniques currently are being used for specialty crops. Table 3 summarizes some relevant applications published in the past two decades.

5.1. NIR spectroscopy

According to the IUPAC definition (Sheppard et al., 1985), NIR radiation covers the range of the electromagnetic spectrum

Table 3
Relevant applications of NIR- MIR spectroscopy in specialty crops.

Category	Subject	Reference
NIR	Dry matter content of onions	Birth et al. (1985)
	Soluble solids content of apples	Bellon-Maurel (1992)
	Water content of mushrooms	Roy et al. (1993)
	Acidity, soluble solids, and firmness of apples	Lammertyn et al. (1998)
	Detection of brown heart in apples	Clark et al. (2003)
	Prediction of the sensory quality attributes of apples	Mehinagic et al. (2004)
	Prediction sensory attributes of chicory	François et al. (2008)
	SRS for measuring the sugar content and firmness of apples	Peng and Lu (2007)
	Estimation of water and chlorophyll content	Cubeddu et al. (2001)
	TRS for modeling nectarine softening	Zerbini et al. (2006)
MIR	ATR-FTIR for detecting sugars and acids in tomatoes	Beullens et al. (2006)
	ATR-FTIR for detecting sugars and acids in apples	Rudnitskaya et al. (2006)
	Detection of changes in macromolecular constituents of hazelnut	Dogan et al. (2007)
	Quantification of olive oil acidity	Inon et al. (2003)

between 780 and 2500 nm. In NIR spectroscopy, the product is irradiated with NIR radiation, and the spectrum of the reflected or transmitted radiation is measured. The spectral characteristics of the incident ray are modified while it passes through the product due to wavelength dependent absorption and scattering processes. This change depends on both the chemical composition and the physical properties of the product (Nicolai et al., 2007). Advanced multivariate statistical techniques such as partial least squares regression (PLS) are then applied to correlate the NIR spectrum to quality attributes such as the sugar content or firmness of the product. This relation can be used to calculate the quality attributes of future samples from their NIR spectrum.

NIR spectroscopy has been used for rapid analysis of mainly the moisture, protein and fat content of a wide variety of agricultural and food products (Gunasekaran and Irudayaraj, 2001; Butz et al., 2005). While early applications in horticulture focused on the dry matter content of onions (Birth et al., 1985), the soluble solids content (SSC) of apples (Bellon-Maurel, 1992) and the water content of mushrooms (Roy et al., 1993), many other applications have followed. As the propagation of NIR radiation in fruit and vegetable tissue is affected by its physical properties and notably its microstructure, NIR spectroscopy has also been used to measure microstructure related attributes such as stiffness (Lammertyn et al., 1998), internal damage (Clark et al., 2003), and even sensory attributes (Mehinagic et al., 2004; François et al., 2008). A comprehensive overview of applications of NIR spectroscopy to measure quality attributes of fruit and vegetables was recently published (Nicolai et al., 2007). It includes a comprehensive table with the most relevant and recent applications, up to 2007. A very large number of papers have been published in recent years concerning NIR spectroscopy in foods, and specialty crops are one of the beneficiaries, and the most recent papers usually contain good reviews on the matter (Liu et al., 2010).

The information related to the physical (scattering) and chemical (absorption) properties of the biological tissue is combined within the NIR spectrum. Both space-resolved and time-resolved techniques have been used to separate the scattering and absorption information. In space-resolved spectroscopy (SRS), a camera is used to acquire a hyperspectral image of a spot of light which is projected on the surface of the fruit. The size of the reflected spot is larger than the projection area because of scattering, and may depend on the wavelength. The hyperspectral image can then be correlated to the quality attributes of the product. This technique has been used with good result for measuring the sugar content and firmness of apple fruit (Peng and Lu, 2007). In time domain reflectance spectroscopy (TRS), series of very short (picosecond or femtosecond) NIR light pulses are illuminated into the fruit using a tunable laser or a solid state laser array (Cubeddu et al., 2001). The detector is positioned at some distance from the light entry point

of the incident photons. Depending on the scattering properties of the tissue, the photons may follow a complicated path in the tissue and it may take more or less time to reach the detector. As a result, the detector will measure a photon time-of-flight distribution from which, based on light diffusion theory, the absorption and scattering coefficient as a function of wavelength can be measured. These coefficient spectra can then be correlated with internal quality attributes. So far the obtained correlations between absorption and scattering spectra and quality attributes such as SSC or firmness were low (Valero et al., 2004; Zerbini et al., 2006) to non-existent (Nicolai et al., 2007), most probably due to instrument drift or the limited wavelength range ($\leq$1030 nm) considered in the experiments. In the same context as TRS and SRS there is recently an increasing interest towards calibration techniques which rely on the actual physics of penetration of NIR radiation in fruit tissue rather than on a pure statistical analysis such as PLS on empirically preprocessed spectra. Advanced light transport simulation models based on the diffusion approximation, the adding–doubling method or the Monte Carlo method might guide these research efforts, and make it possible to separate the information related to the physical (scattering) and chemical (absorption) properties of the biological tissue (Saeys et al., 2008).

Most applications of NIR spectroscopy which are described in the literature essentially rely on spot measurements. The availability of affordable hyperspectral cameras and spectrographs has provided exciting new possibilities for online defect detection which are not feasible with visible light, such as detection of defects which are difficult to observe in the visual range of the spectrum such as early bruises in apple fruit (Xing and De Baerdemaeker, 2005). While acquisition speed is still an issue, focal plane array cameras may solve this problem. NIR microscopes implementing this technology have appeared recently, and it is expected that they will provide a better understanding of the microscopic distribution of, e.g., sugars or other interesting biochemical components at the histological or cellular level.

The availability of fast and relatively cheap diode array spectrometers which allow to acquire an NIR spectrum in as little as 50 ms has boosted research and development towards commercial applications, and grading lines equipped with NIR sensors are now commercially available from different manufacturers. More widespread use of this technology depends on several factors, of which model robustness is the most important technical one. Obviously, the accuracy of the NIR calibration models should be sufficient even when they are used to predict quality attributes of product specimen which were not used in the model calibration. Calibration models to be used in practice should be based on large datasets, encompassing several origins, climate conditions, seasons and operational conditions such as temperature, and optimised towards robustness by incorporating appropriate spectral prepro-

cessing methods. Protocols are needed to update calibration models with minimal effort. Other issues which have to be considered are temperature sensitivity of NIR measurements (Roger et al., 2003) and transfer of a calibration model to a different spectrophotometer (Greensill et al., 2001).

5.2. Mid-IR spectroscopy

Mid-infrared spectroscopy addresses the interaction of matter and electromagnetic radiation with a wavelength between 2.5 and 25 µm. Absorption of Mid-IR light results from transitions between vibrational and rotational energy states of molecules. Mid-IR spectra are commonly acquired by means of Fourier Transform IR spectrometers (FTIR). The main advantage of Mid-IR in comparison to NIR spectroscopy is the fact that the Mid-IR spectrum is much less convoluted than the NIR spectrum; the peaks are much sharper and can often be directly associated with specific chemical constituents. However, an inherent problem in Mid-IR spectroscopy is the limited penetration depth. While for NIR radiation the penetration depth in biological tissue is of the orders of cm in the so-called optical window between 700 and 900 nm, it rapidly decreases to 1 mm or less at 1600 nm, and in the Mid-IR range it is only fractions of a millimeter (Lammertyn et al., 2000). FTIR spectroscopy is therefore mainly used to characterize homogeneous samples such as juices, often in combination with an attenuated total reflection (ATR) sample presentation accessory. ATR-FTIR has been used to detect sugars and acids in tomatoes (Beullens et al., 2006) and apples (Rudnitskaya et al., 2006), to detect changes in macromolecular constituents of hazelnut (Dogan et al., 2007), and to quantify olive oil acidity (Inon et al., 2003). Mid-IR spectroscopy seems to be more appropriate for qualitative (classification) purposes or to detect adulteration rather than for the quantitative measurement of quality attributes of agricultural products.

5.3. Fluorescence and delayed-light emission (DLE)

Fluorescence and phosphorescence are summarized by the term "*photoluminescence*". To activate a luminescence response in a body, excitation is accomplished by short-wavelength light, traditionally in the UV, but also in the VIS range. Most applications of fluorescence in plants that have been published are related to the determination of chlorophyll activity. DLE is fluorescence that develops shortly after excitation, due to intermediate reactions in photosynthesis (Butz et al., 2005).

Applications of fluorescence reported in the literature have been related to chlorophyll, as an indirect marker for fruits' physiological status: chlorophyll degrades in fruits, and also in vegetables, as a consequence of ripening, senescence, time and treatments. Butz et al. (2005) include references regarding applications in: freshness of broccoli, postharvest defects in apples, cold damage in oranges, and senescence in cucumber. Some chemicals in plants, different from chlorophyll, fluoresce, like phenolics. As fluorescence response is dependent on the excitation wavelengths and the response is also wavelength dependent, the technique shows a potential high specificity of the response of different compounds. Hyperspectral devices have been used to characterize fluorescence responses, e.g., for the characterization and differentiation of edible oils of plant origin using lasers as excitation source (Kim et al., 2001; Sikorska et al., 2005). Slaughter et al. (2008) used visual and machine-vision methods for early detection of frost damage in oranges. Fluorescence is a promising technique, widely used in chemistry, which could be the basis for new specialized sensors. However, substantial research is needed in the basic science of fluorescence to advance possible applications, as well as in the instrumentation and its applicability in practice.

Some publications show the applications of fluorescence imaging for detection of quality of fruits (Liu et al., 2008; Valcke, 2008) even integrating it with conventional reflectance (Noh et al., 2007). They use a laser as fluorescence-inducer, and hyperspectral imaging for capturing. More in-depth knowledge on the fluorescing agents of intact fruits is needed, and their relationship with fruit quality before feasible applications may be developed.

6. Mechanical methods for firmness measurement

Mechanical techniques have been developed to non-destructively measure some quality parameters of fruit and vegetables, mainly for firmness estimation, providing an alternative to the destructive Magness–Taylor penetrometry (García-Ramos et al., 2005; Nicolaï et al., 2006). Major mechanical techniques include the measurement of variables extracted from quasi-static force-deformation curves, the analysis of impact forces, and the measurement of acoustic responses to vibrations and impacts.

6.1. Measuring the variables of force-deformation curves

By applying a small deformation force to the fruit with a metallic plunger in such a way that it causes no damage, the non-destructive force-deformation curve can be recorded using an analogue (spring) or a piezoelectric sensor positioned at the back of the compression plunger. The curve is produced by applying a small load for a fixed period of time (Macnish et al., 1997) or by calculating the force necessary to reach a pre-set deformation (Fekete and Felföldi, 2000). This non-destructive technique (also known as micro-deformation) has led to the development of a number of force-deformation devices.

Micro-deformation sensor developed by Cemagref (French agricultural and environmental engineering research institute) (Steinmetz et al., 1996) consists of a flexible positioning cup with a contact plunger in the centre to slightly deform the fruit surface (maximum 2 mm approx.). A micro-deformation device was developed by Copa Technology in collaboration with CTIFL (Centre Techniques Interprofessionnel des Fruits et Légumes). Their "*Durofel*" instrument has a metallic, flat-ended probe with three possible contact areas (10, 25, 50 cm^2), and is based on the Shore A durometer. The device has been widely used for apricots (Jay et al., 2000), tomatoes (Planton, 1991), cherries (Clayton et al., 1998) and other soft fruits.

Macnish et al. (1997) describe two non-destructive devices for measuring firmness developed by CSIRO (Australia's Commonwealth Scientific and Industrial Research Organization): the Analogue Firmness Meter (AFM) and the Digital Firmness Meter (DFM). These devices have been used with tomatoes and mangos. The fruit is placed in a v-shaped structure, and then a 40 mm diameter disc is applied to it. The disc is joined by an arm to an analogue displacement gauge (Macnish et al., 1997).

A non-spectroscopic method of measuring mechanical deformation with a laser has been developed (Hung et al., 1999). Known as the "*laser air-puff*", this device measures the deformation of fruits subjected to a short but strong current of air (69 kPa in 100 ms). McGlone et al. (1999) used a similar system to test kiwifruit, but only very soft fruit could be accurately distinguished (McGlone et al., 1999). More recently, Lu and Tipper (2009) develop a portable bioyield detection device to measure apple fruit firmness, which measure force at the bioyield point as an indication of fruit firmness.

6.2. Sensors based on force-versus-time measurements (impacts)

There are many ways of using impact sensors, such as: (a) hitting the fruit with some element that includes the sensor; (b) putting

the fruit over a load cell and letting a weight fall on it; (c) placing the fruit on a flat plate with a load cell located beneath it.

Chen and Ruiz-Altisent (1996) developed a "lateral impact sensor" consisting of a small arm with lateral movement that impacts the fruit with a semi-spherical head. A piezoelectric accelerometer located on this head estimates fruit firmness. Lateral impact sensor was adapted for use with a conveyor belt (Chen and Ruiz-Altisent, 1996; García-Ramos et al., 2003). Peach and apple firmness could be measured at a maximum speed of 6 fruits per second. A step forward in this technique was the development of a manual impact sensor shaped like a gun. This sensor can be used in orchards to determine the optimum harvest date (Chen et al., 2000). Delwiche et al. (1996) developed a sensor, based on the impact technique, that acts horizontally and consists of a cylindrical head with an attached accelerometer, all moved by a pneumatic cylinder. The sensor was installed successfully in an experimental packing line (Delwiche et al., 1996).

Impact techniques can also involve dropping the test fruit onto a load cell. Moltó et al. (1996) and Gutiérrez et al. (1999) described a sensor based on this idea, the load cell recording the impact when the fruit falls on it. The sensor, patented in Spain by IVIA (the Valencian Institute for Agricultural Research) and FOMESA (Food Machinery Española, S.A.), has been used to detect puffed clementines online at a speed of 5 fruits per second and with an accuracy of over 90% (Moltó et al., 1996).

All the equipments described above have been developed by research groups and is currently being used in the form of prototypes. However, some companies are marketing various forms of impact apparatus for online use (the sensors used are usually piezoelectric, providing a voltage signal proportional to the impact force in a manner similar to an accelerometer). For example: the impact/acoustic firmness sensor (AFS) by Aweta, Greefa (iFD, intelligent firmness detector), Sinclair iQ firmness tester. These sensors have been tested with apples, avocados, citrus fruits, kiwis, plums, nectarines, peaches and many other fruits (Howarth and Ioannides, 2002). These sensors are capable of measuring 6–10 fruits per second. Bench-top versions of these equipments are commercially available, and handheld versions are being developed for field or on-tree measurements (Slaughter et al., 2009).

7. Acoustic response for firmness and structural defects

Non-destructive techniques of using acoustic and vibrational characteristics for determining internal properties of fruits and vegetables, mainly flesh texture, have been the subject of numerous investigations over the past several decades. In order to obtain an objective and non-destructive measurement of firmness, several techniques (Chen and Sun, 1991; Abbott, 1999) and theoretical models (Huarng et al., 1993) about the dynamic behavior of these biological materials were developed many years ago. These models mainly assume that the object is spherical and approximately elastic. Cooke and Rand (1973) proposed a mathematical model for the modulus of elasticity:

$$E = C \cdot f^2 \cdot m^{2/3} \cdot \rho^{1/3},$$

where E is the coefficient of elasticity (Pa), C is a constant, f is the frequency for the highest amplitude (Hz), m is the mass and ρ is the density (kg m^{-3}). Since the 1990s several research groups (Chen et al., 1996; Abbott et al., 1997) and others have done extensive research on simulating sonic vibrational behavior for different shapes of fruits.

In these techniques, the product is excited by means of a small impact, and the vibration (about 20–20,000 Hz) is measured using a microphone, piezoelectric sensors or laser vibrometers. The acoustic signal captured is Fourier transformed and the main frequencies

calculated. Resonant frequencies observed in the fruit relate to elasticity, density, size and shape of the object. Resonant frequencies of some fruits and vegetables (apples, melons, peaches, tomatoes, etc.) have been associated with firmness using coefficients described as "*stiffness coefficient*" or "*firmness coefficient*". The stiffness coefficient was formerly defined as $f^2 m$, where f is a selected resonant frequency, and m is the mass of the fruit. This was later corrected and replaced by the expression $f^2 m^{2/3}$, but in recent works $f^2 m$ has been applied (Fekete and Felföldi, 2000). Depending on the published applications, f can be the first, second, third, or the highest resonant frequency, or any other combination. In the determination of peach firmness, the second resonant frequency is used (Clark and Shackelford, 1973); for testing the texture of apples, the second or third resonant frequencies can be used (Abbott and Liljedahl, 1994), for pineapples the first resonant frequency is used by some authors (Chen and De Baerdemaeker, 1993) and the third one is proposed (Pathaveerat et al., 2008), while for pear the second frequency is considered (Taniwaki et al., 2009b). A handheld prototype was developed to measure firmness while the fruits were still on the tree using the stiffness factor $f^2 m^{2/3}$ (Zude et al., 2006).

These coefficients and their theoretical basis are appropriate for regular shapes (sphere, axisymmetric spheroid), but they are also applied to more irregular fruit shapes. If the fruit or vegetable shape is far from spherical, adapted firmness indices including a measure of shape is proposed by some authors (Jancsók et al., 2001).

Correlations between the textural characteristics of fruits and vegetables and other vibration or sonic variables, e.g., pulse propagation velocity, damping coefficient and band magnitude, have also been studied earlier (Garret and Furry, 1972; Sugiyama et al., 1998) and recently (Taniwaki et al., 2009a).

Non-destructive techniques using sonic characteristics of fruits and vegetable have been applied also for detecting internal disorders and classification: internal creases or voids in seedless watermelons by impacting the fruit (Diezma-Iglesias et al., 2004) dropping potato tuber onto an instrumented surface (Elbatawi, 2008), or sorting pistachio nuts with closed shells from those with open shells (Pearson, 2001).

Several commercial sonic devices have been also developed: the AFS by Aweta, mentioned before, is a good example that combines acoustic and impact responses: the excitation impact is generated mechanically on the bottom of the fruit and a microphone records the vibration. Both responses, impact and acoustic, are used in dedicated algorithms which are able to measure firmness of apples in a large range accurately (Herrero-Langreo, 2010). The combination of two and more types of different sensors, mainly for fruit ripeness assessment has been stressed for long time. Ruiz-Altisent et al. (2006) showed that in peaches, up to 91% of the total variability in ripeness was obtained by combining optical (VIS) and mechanical measurements (optical reflectance). This opens a new way for increasing the accuracy and robustness of sensors in practice.

8. Chemical sensors

There is a need for quick testing for both individual chemical compounds and composite mixtures of different nature (Snopok and Kruglenko, 2002); also a non-destructive, non-invasive approach is desirable, able to correlate information available on the product with the stage of freshness and quality. Low-cost and continuous monitoring of chemical and microbiological quality (including microbiological examination of food: aerobic colony count, presence and/or number of pathogens), with fast response times, can be achieved with chemical sensors.

8.1. High selectivity versus low selectivity sensors

According to the International Union of Pure and Applied Chemistry (IUPAC) nomenclature, "a chemical sensor is a device that transforms chemical information, ranging from the concentration of a specific sample component to total composition analysis, into an analytical useful signal. Chemical sensors usually contain two basic components connected in series: a chemical (molecular) recognition system (receptor) and a physico-chemical transducer" (Snopok and Kruglenko, 2002).

Chemical sensors may be classified according to the chemical specificity-conferring mechanism; biosensors are a subgroup of chemical sensors which incorporate a biological or biomimetic sensing element. The main biological materials used in biosensor technology are the couples enzyme/substrate, antibody/antigen and nucleic acids/complementary sequences. The selectivity of the biological sensing element offers the opportunity for development of highly specific devices for real-time analysis in complex mixtures (Velasco-Garcia and Mottram, 2003). The most important area of interest for the biosensor application is the detection of pathogens, pesticides, microorganisms and toxins (Mello and Kubota, 2002).

Typically, a "lock-and-key" approach is not suitable for simulation of human preferences to the composition of complex mixtures as foods or beverages. Snopok and Kruglenko (2002) described a multi-component chemical media (MCM) not by a sum of their individual components (or corresponding responses from the specific sensors) but by some abstract representation, a chemical image (CI) as a fingerprint where a set of parameters characterize a given MCM. An "electronic nose", which mimics the human olfaction, is an example of "electronic sensing" based on arrays of low-selective/cross-reactive sensors, which combined responses and coupled with an appropriate pattern recognition system, allow characterizing a gaseous sample as a global fingerprint or chemical image.

9. Biosensors

The biological recognition element of a biosensor can be classified into two main classes: biocatalysts (enzymes, microorganisms, tissue materials) and bioligands (antibodies, nucleic acids, lectins). The traditional transducers are electrochemical, optical and thermal. The latest generation of biosensors (affinity biosensors) combine the classical measurement principles with piezoelectric and magnetic transducers (Castillo et al., 2004).

More than 10 years ago Lowe (1999) already expressed that "there is a general consensus that a number of new opportunities for biosensors are appearing in agri-food production and process monitoring". In the specific case of postharvest management of specialty crops, the most important concerns are the following issues (summarized in Table 4).

(1) *Detection of pesticide residues.* Enzyme bioreceptors are widely employed for this application. Amine et al. (2006) estimate that about 71% of the applications described for these enzymatic biosensors are for the determination of pesticides including carbamates and organophosphorus compounds, while heavy metals detection represent only 21%. These biosensors are based mainly on the inhibition of Acetylcholinesterase (AchE), but using different signal transduction methods. Velasco-Garcia and Mottram (2003) presented in their review some practical applications: pH-sensitive transducers were successfully applied to the quantification of the pesticide propoxur in onion and lettuce samples, for the determination of heavy metal ions and phosphororganic pesticides in contaminated potatoes and a biosensor based on AchE immobilized onto magnetic particles in a photometric flow injection system could detect methamidophos (organophosphate insecticide) in lettuce and cabbage. More recently Nagatani et al. (2007) have developed pesticide residue detection visual chips based on AchE, which could differentiate between concentrations of 0.1 and 0.2 ppm of diazinon–oxon in real samples of apple and orange juice.

(2) *Quality control in storage atmospheres.* Determination of ethanol is important in agricultural and environmental analysis as for example in modified-atmosphere packages and controlled-atmosphere storage as a technique for low oxygen injury detection during the handling of fruits and vegetable (Velasco-Garcia and Mottram, 2003). The most promising ethanol sensors developed up to date are the bienzymatic sensors based on the co-immobilization of the enzymes alcohol oxidase with horseradish peroxidase, bienzymatic system that has been used to develop commercial colorimetric sensors which are able to detect low-O_2 injury in modified-atmosphere packages containing fresh cut fruits and vegetables (Azevedo et al., 2005).

(3) Foodborne pathogen and toxins detection in fruits and vegetables. According to Lazcka et al. (2007) biosensors are at the present the fastest growing technology for pathogen detection, being possible in a near future that this analytical technique can replace the reference test ELISA. This is a great interest area not only due to their potential toxicity detection, but also due to being indicators for freshness or spoilage of fruits and vegetable (Saaid et al., 2009; Velusamy et al., 2010). Nayak et al. (2009) in their review, present an application of light scattering biosensors for the detection of target bacteria viz. *L. monocytogenes*, *E. coli* O157:H7 and *Salmonella* in vegetable and meat samples spiked with these bacteria. The forward scattering was able to detect the presence of contaminants accurately based on the distinct colony/scatter signature. The detection limit of this system was single cell per 25 g portion of test specimen. On the other hand moulds of the genera Aspergillus and Penicillium occur in different fruits, producing several mycotoxins than have been described as toxinogenic. Leung et al. (2007) in their review about fiber-optic biosensor described a fluo-

Table 4
Main objectives and technologies involved in biosensing.

Objectives	Technologies	References
Detection of pesticide residues	Enzyme bioreceptors pH-sensitive transducers Pesticide residue detection visual chips based on AchE	Amine et al. (2006) Velasco-Garcia and Mottram (2003) 2007
Quality control in storage atmospheres	Co-immobilization of the enzymes alcohol oxidase with horseradish peroxidase	Azevedo et al. (2005)
Foodborne pathogen and toxins detection in fruits and vegetables	Optical-based biosensors Light scattering biosensors for the detection of target bacteria viz. *L. monocytogenes, E. coli* O157:H7 and *Salmonella* Fluorescent sensor to detect fumonisins and aflatoxins Antennae of Colorado potato beetle for detecting *Phytophtora infestans*	Velusamy et al. (2010) Nayak et al. (2009) Leung et al. (2007) Velasco-Garcia and Mottram (2003)

rescent sensor to detect fumonisins and aflatoxins in maize, using a competitive assay, on the one hand, to measure fumonisin B-1 (FB1); the antibody to FB1 was covalently bonded to the fiber, the fluorescence signal was inversely proportional to the concentration of FB1. On the other hand the mycotoxin aflatoxin B-1 (AFB(1)) was detected using a non-competitive assay because the AFB(1) fluoresces. The fluorescent signal in this case was directly proportional to the concentration of AFB(1). The detection limit was 2 ng/mL of AFB(1). A biosensor based on the intact antennae of Colorado potato beetle (*Leptinotarsa decemlineata*) was developed to detect marker volatiles released by potato tubers infested with *Phytophtora infestans* fungus (aflatoxins producer). The biosensor was able to detect one single diseased potato tuber within up to 100 kg potato tubers (Velasco-Garcia and Mottram, 2003).

In spite of the applications described in previous paragraphs, there are relatively few publications on biosensors applied in postharvest technology. The extended review by Rich and Myszka (2007) on commercial optical biosensors, shows 14 papers under "*Food*, *agricultural*, *veterinary* and *environmental sciences*". Among them there are no applications reported on fruit and vegetable postharvest control quality.

An important remark is that the majority of the biosensors cited are to be used in a liquid phase (sometimes used to build the equipment called "*electronic tongues*"), showing that the non-destructive approach is still far in the case of solid samples. In general among other drawbacks that biosensors have to overcome are the limited lifetime of the biological components, the lack of selectivity in real complex matrices, the improvement of the sensor devices (in sensitivity and in reproducibility) and the cost for mass commercial production.

9.1. Electronic nose

The concept of the electronic nose (EN) was already formulated by Gardner and Bartlett in 1993 as an instrument capable of recognizing simple or complex odors. It is possible to build a fingerprint that represents the global effect of the aroma food sample, with the sensor array response for the interaction of the aroma components with the receptor sites in function of the chemical specificity-conferring mechanism and the mode of physico-chemical signal transduction (semiconductor, transistor and piezoelectric transducers are the most used) (Snopok and Kruglenko, 2002).

From the postharvest management point of view, in fruit ripeness the most important changes in fruit aroma are experienced during the shelf-life period (Brezmes et al., 2001b), but a number of other factors influence volatile emission after fruit storage, mainly storage treatment including period as well as O_2 and CO_2 concentrations in the storage atmosphere. Fruit aroma, or any other volatiles related to the process, are potential indicators of the physiological condition of the fruit, which can be used to develop consistent and reproducible non-destructive techniques to evaluate fruit quality from harvest to consumer (Pathange et al., 2006).

The technique of global aroma analysis by means of EN has been considered very promising during the last 15 years as a non-destructive tool to evaluate fruit quality, as shown in the comprehensive review of Peris and Escuder-Gilabert (2009), from different points of view: shelf-life investigation to assess "Jonagold" (Saevels et al., 2003) and "Pinklady" (Brezmes et al., 2001a) apples quality during shelf-life, to monitor tomato fruit with different storage time (Gómez et al., 2008); harvest date determinations in mandarins (Gomez et al., 2006), apples (Saevels et al., 2003) and mango fruit (Lebrun et al., 2008), to classify "Gala" apples at harvest in different maturity degrees (Pathange et al., 2006), faults detection as to detect freeze damage in oranges (Tan et al., 2005)

or apples defects as mealiness and skin damage in "Cox" (di Natale et al., 2001) and "Red Delicious" apples (Li et al., 2007), and for blueberry fruit disease detection and classification (Li et al., 2010).

Nevertheless at the current stage the expectations have not been achieved in a majority of applications. Both the headspace generation from the sample and the response of sensors, depend on numerous factors that are very difficult to control. The efficiency at generating the headspace is generally low due to external parameters such as temperature or relative humidity and the gas/volatile composition of the environment. In addition important internal parameters, as the nature of the substrate, affect the headspace generation. Concerning the sensors characteristics, common restrictions can be summarized as: lack of sensitivity, lack of linearity, lack of specificity and short- and long-term time drifts. Thus, further research is being carried out to overcome these constraints: basic knowledge of gas/volatiles mixtures and interactions and improvements in the gas transfer components.

In spite of the optimism for the potential of biosensors with a great number of publications on biosensors applied in food analysis, their emergence from the research laboratory to the market has been slow and only a few systems are commercially available.

On the other hand commercial ENs are available in several shapes such as portable (handheld) devices (e.g., 4200 Portable zNose of Electronic Sensor Technology, LP), but mainly as laboratory instruments (e.g., FOX series of ALPHA M.O.S. or LibraNOSE of Technobiochip) using matrix arrays ranging from 8 to 32 sensors. However, the above-mentioned restrictions (headspace generation and sensors response) are obviously the cause of difficulties arising when trying to achieve robust sensor correlations with reference techniques (Mielle and Marquis, 2001). As a consequence, it is not possible to use systematically the EN, not even in industry quality laboratories, without previously carrying out an exhaustive study to identify, control and eliminate those sources of variation that affect the EN measurements for every specific application. Che Harun et al. (2009) proposed a new architecture for a new generation of electronic noses named e-Mucosa. The system combines two odor separation columns with three miniaturized sensor arrays of 200 chemoresistive sensors each, in a portable device with integrated electronics and microfluidic components. A new dimension appears in the data matrix, working with the pattern recognition system in this case with spatio-temporal signals.

The construction of integrated systems that use an array of chemical sensors for electronic nose devices or auto-analyzers of high specificity needs: (1) to design new sensor technologies (sensitive layers, transducers) or to improve the existing ones, and to improve the automated manufacturing technologies to eliminate batch-to-batch variability so as to make them appropriate for commercial mass production, and (2) the integration of the sensor array with an appropriate sample extraction system, fluidics, sensor/sample interface and dedicated electronics. These systems should be coupled to Multisensor Data Fusion (MDF) technology (including signal processing, pattern recognition, statistical estimation, artificial intelligence, and control theory) to fuse data from multiple sensors in order to improve the accuracy of the estimation of the environment (Huang et al., 2007). Finally, there are at least two other developments that are expected to have significant impact in the area of (bio)sensors: the laboratory in a chip, and nanotechnology: metal-oxide semiconducting nanowires or nanotubes can be used for the construction of, for example, gas sensors and electrochemical biosensors. These quasi-one-dimensional nanostructures are essential for the advancement of chemical sensors and will have important impact on the exploration of nanoscale devices, sensors, and detectors using electric, optical, electrochemical and magnetic transducers (Liu, 2008; Xia et al., 2010), for the fabrication of credit-card sized microlaboratories and even for in vivo detection.

Table 5
Summary of recent wireless sensing technology (WST) applications in specialty crops.

Category	Subject	Reference
WSN	Sensor network configurations and applic ations for vineyards	Burrell et al. (2004)
WSN	addressing heat summation and potential frost damage in wine production	Beckwith et al. (2004)
WSN	ZigBee based remote sensing network	Morais et al. (2008)
WSN	Pest control. Fighting *phytophtora* in a potato field	Baggio (2005)
WSN	Distributed greenhouse control	Gonda and Cugnasca (2006)
WSN	Monitor and control the environment in greenhouses with melon and cabbage	Yoo et al. (2007)
WSN	Measuring substrate water, temperature, electrical conductivity, daily photosynthetic radiation and leaf wetness in real-time	Lea-Cox et al. (2007)
WSN	Monitoring system based on ZigBee for greenhouses	Zhou et al. (2007)
WSN	Measuring differences in spatial temperature and humidity in Greenhouse Horticulture	van Tuijl et al. (2008)
RFID	Imaging and environmental sensing in greenhouses	Yang et al. (2008)
Wireless sensor node	Monitoring greenhouses	Wang et al. (2008)
Wireless sensor node	Measuring soil parameters in precision horticulture (temperature, humidity, salinity and electrical conductivity)	Lopez et al. (2009)
WSN	Monitoring refrigerated chamber in wholesale storage	Ruiz-Garcia et al. (2008)

10. Wireless sensing in specialty crops

The use of wireless sensor technologies (WST) in specialty crops offers new features both in terms of sensing and communications that never have been available before. Recent advances in wireless sensor networking (WSN) technology have led to the development of low-cost, low power, multifunctional sensor nodes. Sensor nodes enable environment sensing together with data processing. They are able to network with other sensors systems and exchange data with external users. The application of this technology for monitoring crops that are intensively cultivated is new, since the necessary hardware has only recently become available. However, some applications have been demonstrated for specialty crops (see Table 5).

WSN is one of the most significant technologies in the 21st century. RFID was developed for identification purposes, but growing interest in the many other possible applications has led to the development of a new range of wireless sensor devices based on RFID. The main difference between a WSN and a RFID system is that RFID devices have no cooperative capabilities, while WSN allow different network topologies and multihop communication. A multihop network is dynamically self-organized, with the nodes establishing and maintaining mesh connectivity among themselves. Motes (small single nodes) can form networks and cooperate according to various models and architectures. They come with miniaturized mounted sensors that allow, in a small space ($2.5 \, cm \times 5 \, cm \times 5 \, cm$), the gathering of data not only just about temperature, but also relative humidity, acceleration, shock and light (Ruiz-Garcia et al., 2009). In the case of RFID, there are commercial active and semi-passive tags that can collect temperature information (Amador et al., 2009; Jedermann et al., 2009). Other semi-passive tags outfitted with sensors are under development, like for humidity (Chang et al., 2007; Abad et al., 2009), shock/vibration (Todd et al., 2009), light (Cho et al., 2005; Abad et al., 2009), pH (Steinberg and Steinberg, 2009) and concentration of gases such as acetaldehyde or ethylene (Vergara et al., 2006). Biosensor tags are also being investigated. These tags could be used for detecting bacterial contamination in food products along the supply chain (Wentworth, 2003).

Another advantage for wireless sensor devices is the feasibility of installation in places where cabling is impossible, such as large fields (Morais et al., 2008) or embedded within the implements, which brings their readings closer to the true in situ properties of crops (Ruiz-Garcia et al., 2009).

Most of the applications of wireless sensors in specialty crops have been in monitoring environmental and growing conditions, in field and in the greenhouse. Only with a WSN is it possible to monitor a whole orchard deploying 20 or 30 sensors per hectare, or track the temperature in each flower pot in a greenhouse; these may be distributed in plots averaging for example 4 ha in size and situated up to 10 km apart (Lopez et al., 2009). In these situations, monitoring is impossible with standard cabling technologies. Different configurations have been investigated for monitoring vineyards: (Burrell et al., 2004) described a variety of sensor network configurations and applications that can address different priorities in the vineyard; in field experiments up to 198 sensors and 50 nodes were deployed in about 9 ha of vineyards to send data to a remote server (Bencini et al., 2009).

Beckwith et al. (2004) implemented a WSN consisting of 65 motes of 916 MHz, with the aim of addressing two important parameters in wine production: heat summation and potential frost damage. Morais et al. (2008) showed the feasibility of a ZigBee based remote sensing network, where batteries were recharged with energy harvested from up to three sources (photonic energy, kinetic energy from moving water in irrigation pipes and from wind).

Pest and disease control is an important field for the application of WST in specialty crops: Baggio (2005) deployed a WSN for fighting *phytophtora* infection in a potato field, which depends on the climatological conditions. 868 and 916 MHz motes were used for measuring humidity and temperature coupled with predicting models (Baggio, 2005).

Greenhouse production can greatly benefit from WST. The first application of WSN in a greenhouse was reported in the year 2003; it was a monitoring and control system developed by means of Bluetooth (Liu and Ying, 2003). Since that year, several applications have been developed, most of them making use of IEEE 802.15.4/ZigBee protocol (IEEE, 2003; Gonda and Cugnasca, 2006; Lea-Cox et al., 2007; Liu et al., 2007; Yoo et al., 2007; van Tuijl et al., 2008), including multi-spectral imaging for remote sensing of the canopy of seedlings (Wang et al., 2008; Yang et al., 2008).

The most advanced systems integrate a variety of sensors, which can measure substrate water, soil and air temperatures, soil electrical conductivity, daily photosynthetic radiation and leaf wetness in real-time. Resulting benefits that have been demonstrated include control for improved plant growth, more efficient water and fertilizer applications, together with a reduction in disease problems related to over-watering, and therefore for optimizing quality of the crops.

Further important applications showing high potential are monitoring fruit and vegetable containers and cold-storage facilities, with or without controlled atmosphere (Ruiz-Garcia et al., 2008) or monitoring quality and senescence of specialty crops during transport (Ruiz-Garcia, 2008). Many other potential applications in the field and greenhouse, and in relation to quality and safety of prod-

ucts and to precision farming, can be envisaged. Wireless sensor technologies hold an important niche in fruit and vegetable quality research laboratories.

11. Summary and conclusions

This review has attempted to provide an overview of existing and promising sensing technologies with an emphasis on their current and future application potential for the specialty crop industry. Several technologies were reviewed, mainly: (1) electromagnetic sensors, spectroscopic and computer vision; (2) mechanical contact and acoustic sensors; (3) biosensors; and (4) wireless sensors networks.

Advances in laboratory instrumentation have made it possible to introduce a variety of sensors for practical applications in specialty crops, but the transfer of the promising, and in many cases proven techniques to the industry is taking place at slow pace. Computer vision-based online fruit grading systems are already in use in Europe and the USA (Kondo, 2010); however, they are only used fort basic color and size measurements. Hence, there are great opportunities for turning these promising or proven techniques into computerized and automated equipment for commercial applications, given that:

- Computer vision linked to robotics has already been demonstrated as a basic component of automated operations in many industries.
- Machine vision is fast, cost-effective and easy to automate, and can operate under rugged, hostile environments.
- Problems such as dust, water spills, product residues or potential light source variations have already be solved in commercial application of NIR-based technology.
- Automation and robotics are already present in some operations for many industries. Unlike conventional machines, automated systems are able to handle a great amount of information. However, understanding of the diversity and complexity of biomaterial properties is needed in development of sensors and their systems.

As computer capabilities and processing speed are continually improving, the emergence of new spectral regions (MIR, X-rays), NMR and photoluminescence, and multi- and hyperspectral imaging is likely to present great opportunities in quality and safety inspection of specialty crops. However, these emerging technologies will need further research efforts in order to meet the online inspection requirements, and such efforts have already begun.

Moreover, there is a need for portable equipment for use in the field and packinghouse as a support for mechanised and automated processes. Portable, on-site sensing networks that integrate information collection, processing and analysis, and management are needed for on-tree monitoring of the quality and condition of specialty crops.

For improving management decisions, sensor networks based on wireless communication show a high capability of increasing sensing capacity for specialty crop production and quality monitoring. Ornamentals production systems have a different infrastructural and commercial environment, and the application of the sensing principles is scarce. However, the techniques presented in this paper, especially computer vision, are shown to be very appropriate for this sector.

Logistics management and traceability need the development of sensors networks which are reliable, easy to implement and of low-cost. RFID readers with onboard environmental and volatiles sensing capabilities, together with flexible tags, show great promise for monitoring product quality and safety in large containers and long-distance transportation.

In conclusion, many sensing technologies have been developed in the past, and further research and development are needed to meet the needs of specialty crop industries. Greater contribution and involvement from the equipment manufacturing industry is essential for moving the developed technologies from research laboratories to specialty crop processing and packing houses. The success of any online technology for sorting and grading fruit and vegetables will be dependent upon its added commercial value for the specialty crop industry. Only when consumers are willing to pay premium prices for, e.g., extra sweet fruit, will auctions and packinghouses adopt such new grading lines and change their quality grading standards that are now almost exclusively based on external appearance.

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