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A Review of Non-Destructive Methods for Detection of Insect Infestation in Fruits and Vegetables

Innovations in Food Research

Review

A review of non-destructive methods for detection of insect infestation in fruits and vegetables

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ABSTRACT

Insect damage in fruits and vegetables cause major production and economic losses in the agriculture and food industry worldwide. Monitoring of internal quality and detection of insect infestation in fruits and vegetables is critical for sustainable agriculture. Early detection of an infestation in fruits can facilitate the control of insects and the quarantine operations through proper post-harvest management strategies and can improve productivity. The present review recognizes the need for developing a rapid, cost-effective, and reliable insect infestation monitoring system that would lead to advancements in agriculture and food industry. In this paper, an overview of non-destructive detection   insect damages in fruits and vegetables was presented, and the research and applications were discussed. This paper elaborated all of the post-harvest fruit infestation detection methods which are based on the following technologies: optical properties, machine vision technique, sonic properties, magnetic resonance imaging (MRI), thermal imaging, x-ray computed tomography and chemical chromatography. Also, the main challenges and limitations of non-destructive detection methods in the agricultural products quality assessment were also elucidated.

1. Introduction

Enormous quantity of fruits and vegetables are infested with insects each year, causing major production and economic losses in agricultural and food industry worldwide. The presence of insect pests in horticultural commodities leads to major disruptions in the storage, processing and shipment of these products. For example, it has been estimated that fruit flies damages could cause annual economic losses of more than $42 million in Africa and $1 billion worldwide, and an infestation of a particular type of fruit fly (*Ceratitis capitata*) in the U.S could cost as much as $1.5 billion yearly due to export sanctions, lost markets, treatment costs and crop losses (FAO 2010; Kendra et al. 2011; USDA-ARS 2005). U.S. appropriations for exotic fruit flies risk management programs are over $57 million per year (USDA-APHIS 2010). In fact, the loss of post-harvest fruits and vegetables in circulation is huge reaching 30%~40% every year (Gao et al. 2010; Lixin et al. 2004) and thus much attention should be paid to the post-harvest processing technology.

The globalization, which led to an increase in the volume of trade in agricultural products, has also brought about the risk of pest invasions to the sanitary regions. Many cases, such as the Mediterranean fruit fly and the Asian long-horned beetle, have proved how alien pests can damage agriculture and ecology (Komitopoulou et al. 2004; Poland et al. 1998). Suitable border control procedures for agricultural products have thus been strengthened in many countries to reduce the propagation of alien pests. Although it has been well addressed that it is substantial to build a secure quarantine system, but most of the monitoring methods in practice rely on visual inspection of external appearance, followed by dissecting examination if suspected. For instance, at the U.S. points of import, incoming produce shipments are checked randomly by manual destructive sampling and searching for larvae (Kendra et al. 2011). These visual inspection methods are laborious, time-consuming and subjective. As a result, there is a need to provide a feasible means to facilitate the quarantine operations by improving efficiency, reliability, and accuracy.

In many countries, zero tolerance regulations for the presence of insect infestation in fruits impose high strains on the food industries by making their entire shipment unmarketable just for the presence of a few infested fruits in a shipment. It is, therefore, important to identify fruits with insect damage before they are shipped to the market. On the other hand, traditional sorting techniques, including manual sorting, are generally inadequate for the detection and removal of fruits with hidden internal damages. Gould (1995) estimated that only about 35% of grapefruits infected with *Anastrepha suspensa* were detected by trained inspectors. Consequently, development of methods which will increase the probability of detection of infestation in imported material is therefore highly sought after.

Insect feeding damages often occur within fruits and vegetables without showing an obvious external symptom until it is nearly fully-mature/ripen. In most cases, adult females have well-developed ovipositors that insert eggs beneath the skin of host fruits and vegetables. Then, the eggs hatch into larvae which feed on the decaying flesh of the fruit. While some infected samples can be identified by visual inspection based on the presence of external pest marks, such as holes or punctures, there are cases in which no visible external marks or holes are present for the damaged fruits. As a result, noninvasive methods of detection are needed to monitor the internal quality of fruits.

With the rapid development of technology and computer science application in the agricultural field, new methods of non-destructive detection of insect infestation of fruits and vegetables have emerged. A variety of techniques have been reported for non-destructive detection of infestation, including those based on near-infrared (NIR) spectroscopy (Saranwong et al. 2011); Acoustic method - sound/noise/vibration (Liljedahl and Abbott 1994); imaging - nuclear magnetic resonance (Zhang and McCarthy 2013), x-ray (Haff and Toyofuku 2008); volatile emission and others (Burn and Ciurczak 2008; Nicolaï et al. 2007; Rajendran 2005; Singh et al. 2010; Sun 2010; Wang et al. 2011). With this new application of technology in agricultural processing and as well as the multiplicity of investigations all over the world, up-to-date reviews are needed to offer an orientation over technological applications at the interface of horticulture and food science. There is currently no reference paper reviewing and collating the state-of-the-art based on previous research and current works being done in the non-destructive detection of insect infestation in fruits and vegetables. Thus, in this present paper, all known techniques used for non-destructive detection of

internal insect infestation in fruits and vegetables are reviewed and the main merits, as well as the limitation of each method, were reported in order to establish the most feasible applications for each method.

2. Electromagnetic energy based technologies

Electromagnetic radiations are free electromagnetic waves, which are the result of oscillations of electrical charges. The electromagnetic spectrum, as shown in Fig. 1 consists of several regions, including gamma rays, x-rays, ultraviolet radiation (UV), visible light (VIS), infrared radiation (IR) divided into near-infrared (NIR), mid-infrared (MIR), and far-infrared (FIR) regions microwaves and radio waves (FM and AM). Each region corresponds to a specific kind of atomic or molecular transition corresponding to different energies. If subjects are illuminated with a suitable range of the electromagnetic spectrum, certain wavelengths are absorbed and transmitted, and this spectrum can be recorded. These spectra are characteristic of atoms, functional groups, and also large molecules and permit statements about the chemical composition of the sample by comparison with spectra from databases. Also, many products are assigned to commercial grades according to their color, and the main absorbing molecules in the visible range (380 to 770 nm) are pigments such as chlorophyll, carotenoids, and anthocyanins. Near-infrared spectrophotometry (NIRS) had been examined as a nondestructive method for the determination of firmness, freshness, Brix value, acidity, color, and other characteristics of many fruits, and from the results achieved, NIRS could be judged as an appropriate method for these applications. X-ray and gamma-rays were examined for their suitability for quality assessment of horticultural products and both kinds of radiation penetrate material bodies and the shorter the wavelength, the larger is the penetration strength. Examples of internal damages detectable by x-ray techniques include cork spot, bitter pit, water core, brown core, membranous stain, black rot, freeze damage, hollow heart, bruises, and black heart (Sun 2010).
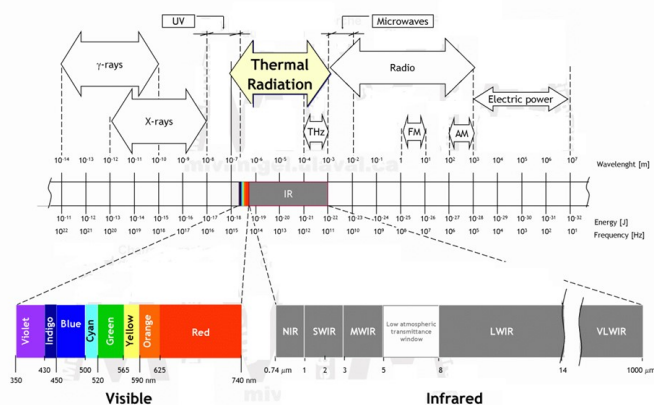

Figure 1. Electromagnetic spectrum. Source: (Ibarra C (https://en.wikipedia.org/wiki/Infrared_vision))

2.1. Spectroscopy techniques

Analysis of optical properties of food products has been one of the most successful non-destructive techniques for quality assessment which provides several quality details simultaneously. Spectroscopy techniques provide useful information about the chemical components and physical properties of fruits and vegetables by obtaining optical characteristics. Optical properties are based on reflectance, transmittance, absorbance, or scattering of polychromatic or monochromatic radiation in the ultraviolet (UV), visible (VIS), and near-infrared (NIR) regions of the electromagnetic spectrum which are measurable by spectral instruments. But, the near-infrared spectrum is especially interesting since it is related to overtones and combinations of such chemical bonds such as C–H, O–H, and N–H, which have the influence on many properties of food for on-line and off-line applications. More importantly, near-infrared spectroscopy has the capacity of measuring multiple quality attributes simultaneously (Sun 2010).

NIR spectroscopy detection of pest infestation is primarily achieved through indirect detection of the changes in the spectral properties of infected tissues, rather than through direct detection of pests present in the tissue. Useful information can be obtained by measuring NIR spectra on the fruit peel, as it can penetrate more than 9 mm with proper wavelength selection (Liu et al. 2011). Thus, NIR spectroscopy has a number of desirable qualities including minimal need for sample preparation and a wide range of applications. Moreover, it is fast, easy to use, environmentally benign, and is highly suited to rapid non-invasive on-line monitoring (Pasquini 2003; Wang et al. 2010). Some research have proven the ability of NIR spectroscopy for the detection of insects or insect damage in food commodities such as blueberry (Peshlov et al. 2009), cherry (Xing et al. 2008; Xing and Guyer 2008), fig (Burks et al. 2000), green soybean (Sirisomboonet al. 2009), jujube (Wang et al. 2010), and others (Burn and Ciurczak, 2008; Nicolaï et al. 2007; Rajendran 2005; Singh et al. 2010).

The high moisture content of fruits and vegetables make it difficult for the light in the long wavelength near infrared range of 1100–2500 nm to penetrate through the whole fruit (Xing and Guyer 2008). Therefore, the short wavelength near infrared (SWNIR) spectroscopy (850–1888 nm) is normally used in internal quality prediction in fruits studies. However, the presence of insect would likely affect other chemical and optical properties of whole fruit as an indirect effect of infection in the tissue that can be detected with vis/NIR spectroscopy. For example, Xing and Guyer (2008) applied visible and near-infrared spectroscopy (550–980 nm) in the transmittance mode to detect plum curculio infestation in tart cherries and achieved an overall detection accuracy of 82–87% (Fig. 2). Their spectral analysis indicates that the maturity of tart cherry has some effects on the classification accuracy and thus, the intact cherries harvested late in the season (over-ripened) have similar spectral characteristics as the infected tissues and as a result, classification accuracy for the samples harvested at right time is better than that for the late harvested samples. Additionally, they suggested measuring total soluble solid (TSS) and firmness as complementary factors for explaining the difference between the insect infected and sound tart cherries and achieve better classification models.

A detailed study on spectral characteristics of healthy and infested tart cherry tissue with and without larvae (*Plum curculio*) for each of UV and visible/NIR light sources was conducted by Guyer et al. (2006). Their results showed that the intensity of transmitted UV signals through the tart cherry was weak; however, the spectral details of UV light in reflectance mode revealed some typical characteristics of larvae on healthy and infected tissue. The larvae on tissue were found to exhibit UV-induced fluorescence signals in the range of 400-700 nm. Their results also showed the shift in peaks of reflected and transmitted signals from healthy and infected tissues and coincide with the concept of browning of tissue at cell level as a process of infestation. Their study was also able to establish the inherent spectral characteristic of these tissues and they concluded that there exist promising futuristic possibilities to use optoelectronic sensing to estimate the degree of secondary effect of insect activities within the tissue.

Peshlov et al. (2009) compared three NIR instruments in diffuse reflectance mode (the low cost system, Ocean Optics SD2000, the research grade Perten DA7000 and a custom-built NIR imaging spectrograph, Oriel MS-257), covering different spectral ranges between 600 nm and 1700 nm, for detecting infestation of wild blueberries by fruit fly larvae. The three instruments showed different infection detection accuracies between 58% and 82%. Wang et al. (2011) evaluated three NIR sensing modes (i.e. reflectance, interactance, and transmittance) for different spectral regions between 400 and 2000 nm for the detection of insect infestation in jujubes. Their results showed that interactance for 1000 – 2000 nm and transmittance for 400–1000 nm had better performance compared to reflectance mode. Saranwong et al. (2011) investigated the potential use of near infrared (NIR) spectroscopy for non-destructive detection of fruit fly eggs and larvae in intact mangoes at different infestation levels. The best classification was achieved using spectra of green mangoes obtained 48 h after infestation, with an error rate of 4.2% for infested fruit and 0% for the 48 control fruit. Their results justified development of an automatic classifica-
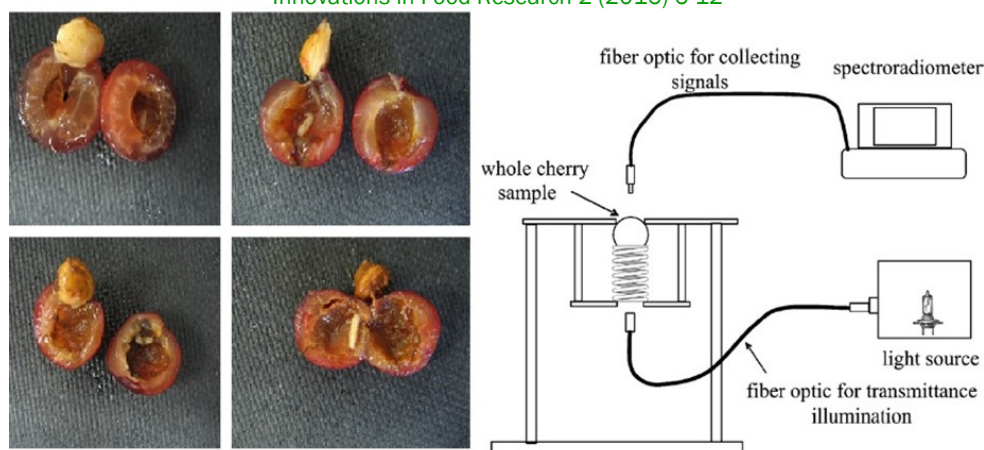
Figure 2. Sketch of spectroscopy set-up (left) and cherry samples in different infestation level (right). Source: Xing and Guyer 2008.

tion and sorting system based on NIR imaging technology (Saranwong et al. 2011).

2.2. Machine vision

Machine vision is an engineering technology that combines mechanics, optical instrumentation, electromagnetic sensing, and digital image processing technology (Sun 2010). Currently, machine vision technology has been widely applied for the detection of external pest damages in agricultural products but because of the challenges involved in penetrating visible light inside of the fruits, it is not effective for detecting internal defects (Lu and Ariana 2013). Generally, fruit infested by some insects has a small exit hole on the surface, suggesting some sort of visible light machine vision to be an effective means of detection. However, some studies have proven this technique to be unreliable because other kinds of surface damage have similar marks that are difficult to distinguish from insect damage (Jackson and Haff 2006; Xing and Guyer 2008) and also, in some cases the stem-end/calyx-end regions of fruits can be misinterpreted as having insect damage (Xing et al. 2007). It is also more difficult to distinguish insect damage at the stem end compared to the other regions of the fruit.

In one study, an automatic machine vision system was developed to detect small insects in a hole of raspberry fruit which were difficult to be found even with human eyes and their results indicated that insects were identified with high success rate but with some failure cases (Okamoto et al. 2013). In another work, a machine vision system algorithm was proposed to determine skin color defects caused by insects based on fuzzy c-means logic with histogram (Moradi et al. 2011). Using this algorithm, they convert the RGB image into L*a*b color space and then active counter model algorithm was applied to extract the fruit shape. Finally, the image was segmented to find defects. The authors achieved 96% of defected pixels and 91% of strong pixels (Moradi et al. 2011).

2.3. Hyperspectral imaging

Hyperspectral imaging is a technique that produces a spatial map of spectral variation of the sample tested, and thus it is a useful tool in different applications in agricultural and food industry (Sun 2010). In hyperspectral imaging, the spectral reflectance of each pixel is acquired for a range of wavelengths (including the visible and infrared regions) as shown in Fig. 3. The resulting information is a set of pixel values (intensity of the reflectance/ absorbance) at each wavelength of the spectra in the form of an image. A hyperspectral imaging system generates a two-dimensional spatial array of vectors which represents the spectrum at each pixel location. The resulting three-dimensional dataset containing the two spatial dimensions and one spectral dimension is known as the data-cube or hypercube (Kim et al. 2002; Schweizer and Moura 2001). Thus, the main impetus for developing a hyperspectral imaging system was to integrate spectroscopic and imaging techniques to enable direct identification of different components and changes and their spatial distribution in the tested sample. Conventional visible/NIR spectroscopy is unable to provide spatial information, which is desirable or even needed in detecting properties or pest-infested tissues that are either spatially variable or are only confined to a small fraction of an area or volume in whole products. Hyperspectral imaging goes beyond conventional imaging and spectroscopy to acquire both spectral and spatial information from an object simultaneously which is advantageous for detecting internal quality attributes, minor or subtle defects, and contamination of horticultural products (Sun 2010). However, some of the major challenges in hyperspectral imaging-based detection are the selection of optimum spectral band and also appropriate statistical classification algorithm for a particular application. In fact, for direct application to automated food processing lines, high-resolution full-spectrum hyperspectral data should be analyzed to carefully select wavelengths relevant to the targeted inspection task to develop a multispectral inspection algorithm suitable for rapid online use.

As a novel, non-destructive technology, hyperspectral imaging covers both visible and near-infrared wavelength information coupled with image information. These features can provide more detection information, including internal structure characteristics, morphology information, and chemical composition, compared with a single machine vision technology or spectroscopy analysis technology. Recently, there
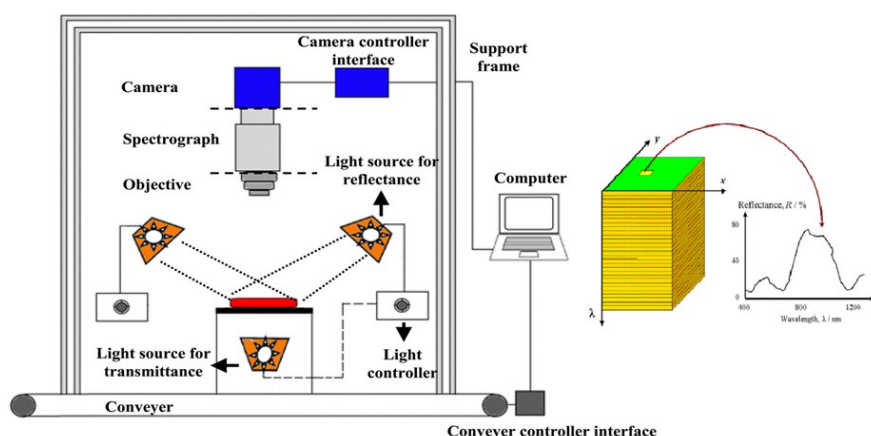

Figure 3. Schematic illustration of the critical components of the hyperspectral imaging system and hypercube.

Table 1. Studies on infestation detection using hyperspectral imaging.

Fruit/vegetable	Insect	Statistical method	Spectral range	References
Soybean	*Etiella zinckenella* Treitschke mothns	Support vector data description (SVDD) classifier	400 – 1000 nm	(Huang et al. 2013)
Pickling cucumbers	Fruitfly	Partial least squares discriminant analyses	(450 –740 nm), (740 –1000 nm)	(Lu and Ariana 2013)
Jujube fruits	-	Stepwise discriminant analysis	400 –720 nm	(Wang et al.2010)
Tart cherries	*Plum curculio*	Genetic algorithm (GA)	590 –1550 nm	(Xing et al.2008)
Mangoes	Fruit fly	Bayesian discriminant analysis	400 – 1000 nm	(Saranwong et al.2011)

are some reports on insect infestation detection using the hyperspectral imaging technology. Table 1 summarizes studies on insect infestation detection using hyperspectral imaging.

Some researchers have also used hyperspectral imaging to identify contaminations on crops as an indirect method of detection of insect infestation. For example, Yang et al. (2014) developed a multispectral fluorescence-based imaging algorithm to detect insect frass contamination on mature tomatoes. The algorithms detected over 99% of the frass contamination spots and successfully differentiated these spots from tomato skin surfaces, stem scars, and stems
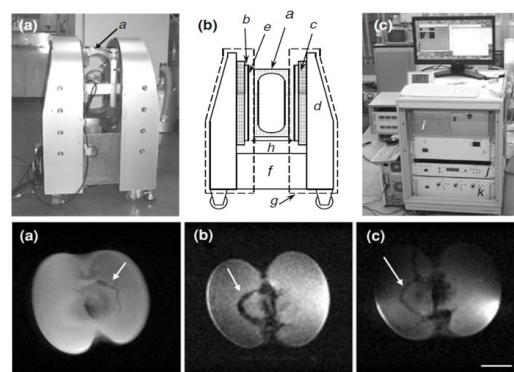
2.4. Magnetic Resonance Imaging

Magnetic resonance imaging (MRI) is useful for investigating the morphology, physiology, and host–parasite interaction of insects, but the drawbacks of MRI for detecting infestation are the large size, heaviness and high costs of current apparatuses along with the difficulties in maintaining operations. These are also the obstacles preventing MRI from being used in the development of other applications in agriculture and food research. In this regard, small, dedicated MRI devices equipped with permanent magnets are thought to overcome a part of this drawback. For instance, low-cost and low-field proton MRI sensors have been recently developed, allowing the rapid sensing of internal monitoring in whole fruit (Butz et al. 2005). The results indicated that it should be possible to use the MRI sensor and conveyor system for online sorting of apples with internal browning at conveyor speeds below 100 mm/s if precise control of the conveyor speed and apple position at the time of interrogation can be maintained (Butz et al. 2005).

Infestation of harvested apple fruits by the peach fruit moth (*Carposina sasakii* Matsumura) was studied using a dedicated magnetic resonance imaging (MRI) apparatus shown in Fig. 4. (Haishi et al. 2011) Infected holes on the three-dimensional images tracked ecological movements of peach fruit moth larvae within the food fruits, and thus in their natural habitat. These results indicate that the 0.2-T MRI apparatus can be used to distinguish sound fruits from infected ones, and also as a means for plant protection and the preservation of natural ecological systems in foreign trade (Haishi et al. 2008)..

Figure 4. The MRI apparatus (up) and the acquired images. Source: Haishi et al. 2011

2.5. Thermal imaging (thermography)

In thermal remote sensing, the invisible radiation patterns of objects in the thermal infrared region of the electromagnetic spectrum (Fig. 1) are converted into visible images (Ishimwe et al. 2014). Thermal imaging utilizes the radiation emitted to produce a pseudo image of the thermal distribution of the surface of a sample. In thermography, a huge number of point temperatures are measured over an area and processed to form a thermal map or thermogram of the target surface. Thermography with high spatial resolution is a powerful tool for analyzing and visualizing targets with thermal gradients. This technology is a non-contact and non-destructive technique used to determine thermal properties and features of any object of interest and, therefore, it can be used in many fields, where heat is generated or lost in space and time. In insect infestation detection, it would function based on chang-

es in surface temperature including temperature differences from entry or exit wounds, feeding tunnels immediately below the fruit surface, disease infections caused by pest feeding, or other damage to the fruit caused by insect activities. However, some drawbacks of this technique compared with other remote sensing imaging are high-resolution thermal imaging are costly and also, accurate thermal measurements depend on environmental conditions.

The possibility of detecting codling moth larvae in apples using thermography have been studied by Hansen et al. (2008). Their results showed that infested sites were visually obvious with the thermograms and the feeding tunnels were consistently cooler than surrounding uninfected areas, regardless if the fruits were maintained at room temperature, were held in cold storage, washed, or any combination of these factors. The location of the infestation site did not alter this relationship, although visual detection at the stem end is more difficult. Statistical tests indicated significant differences in site temperature between infected and uninfected except for those fruits with larvae entrances in the stem cavity and held at room temperature. Differences were greater with the cold fruits than with those held at room temperature. Hansen et al. (2008) concluded that an infrared thermo-imaging process can be a quick, accurate method to detect and sort out apples infested by codling moth larvae.

2.6. X-ray imaging

Although x-ray scanners are widely used in human skeleton scanning and for security inspection reasons, practical application of x-ray imaging in non-destructive inspection of insect pests in fruits is still unavailable due to its costs, the poor penetration of x-rays in materials with high water content and difficulty in effectively differentiating normal and infected tissues (Jiang et al. 2008). As a result, previous x-ray studies in agricultural products mainly focused on x-ray irradiation quarantine treatments (Follett and Armstrong 2004) and on dry or lower water-containing materials, e.g. checking seed quality with soft x-ray radiography (Lammertyn et al. 2003) and for detecting hidden infestation of crop plants. However, with the aid of digitized x-ray imaging analysis, it is possible to examine internal injuries that produce differences from the homogeneity of normal fruit. Since the gray level of x-ray images depends on the density and thickness of the test samples, the relative contrast of infestation site to the intact region inside a typical fruit varies with its position. To accurately determine whether a fruit has signs of insect infestation, an effective adaptive image segmentation algorithm based on the local pixels intensities and unsupervised thresholding algorithm should be developed.

Figure 5. The photograph of automatic x-ray scanner (left), x-ray images of the apple scanned and the segmentation results (right). Source: Chuang et al. 2011

Pioneering work by Reyes et al. (2000) enabled the use of x-ray images to diagnose the mango seed weevil in intact mango fruit by evaluating distinct features of weevil-infested mango seeds. Soft x-ray film imaging was used to predict the presence of mango seed weevil in intact mango fruit. The x-ray film image of a weevil-infested mango has a distinct feature of dark gray patches corresponding to the internal cavities providing positive detection of weevil infestation. X-ray technique has also been researched for pest infestation detection for other horticultural products (Hansen et al. 2008; Jackson and Haff 2006). Hansen et al. (2008) demonstrated that radiographic technology with x-ray could detect internal pests, but the process was imprecise for early life stages, expensive, and relatively slow compared with the rate of fruit processing in commercial packing lines.

Various kinds of fruit were implanted with the eggs of the oriental fruit fly, *Bactrocera dorsalis*, and the x-ray images of the fruit were examined after various time periods (Yang et al. 2006). They concluded that although injuries to fruit created by an insect's ovipositor may be too tiny to be detected by x-ray image analysis, tunnels created by larvae in infested fruit provide a good contrast on the images and are easily detected. The shape of the injury tunnels obviously differs from the internal structures of the fruit, and, in addition to the contrast of the image, the density contours showed remarkable uneven lines or broken areas, indicating that the areas had been damaged by pests and the density had changed.

An algorithm using a Bayesian classifier was developed by Jackson and Haff (2006) to automatically detect olive fruit fly infestations in x-ray images of olives. Internal damage to the olive was a factor in detection; with slight damage correctly identified 50% of the time and severe damage correctly identified 86% of the time. Non-infested olives were correctly identified with 90% accuracy (Jackson and Haff 2006).

A new automatic and effective quarantine system for detecting pest infestation sites in fruits was developed (Fig. 5) and the experimental results showed that the x-ray quarantine scanner and pest infestation detector were able to locate the infested sites with highly successful rate up to 94% on the 4th day after eggs implanted (Chuang et al. 2011).

3. Acoustic

Acoustic devices provide non-destructive, remote, automated detection and monitoring of insect infestations in agricultural products, through sensing of communication, moving and feeding signals of larvae inside post-harvest commodities. The incidental signals that cryptic insects produce while can be very low in amplitude but still detectable by means of acoustic devices with optimized filters and sensors (Fig. 6). In fact, the efficacy of acoustic devices in detecting cryptic insects depends on many factors, including the sensor type and frequency range, the substrate structure, the interface between sensor and substrate, the assessment duration, the size and behavior of the insect, and the distance between the insects and the sensors (Mankin et al. 2011). Problems in distinguishing sounds produced by target species from other sounds and limiting factors such as sensor sensitivity, sensor noise and ambient noise, have hindered usage of acoustic devices. But new devices and signal processing methods have greatly increased the sensitivity and reliability of detection. For example, one new method considers spectral and temporal pattern features that prominently appear in insect sounds but not in background noise, using standard speech recognition tools like Gaussian mixture models (Pinhas et al. 2008; Potamitis et al. 2009) and hidden Markov models (Mankin et al. 2011; Mankin et al. 2009). With the improvement of technology, the reliability and ease of use of available instruments have increased and also costs have gone down. Thus, acoustic devices have considerable future promise as cryptic insect detection and monitoring tools.

While considerable success has been achieved in the identification of grain, trees and wood insect pests, very little attention has been given to the detection of insect infestations in fruits and vegetables. An automatic detector was produced that analyzes acoustic emissions which the red palm weevil larvae produced during eating and feeding inside the trunk of the palm tree and the emissions were parameterized for processing with pattern recognition techniques (Potamitis et al. 2009). The same approaches were also implemented to detect termite's infestation inside trees and to look for black vine weevil larval infestation in nursery containers (Mankin et al. 2002). Similar investigations with the same technique have also been conducted by other researchers
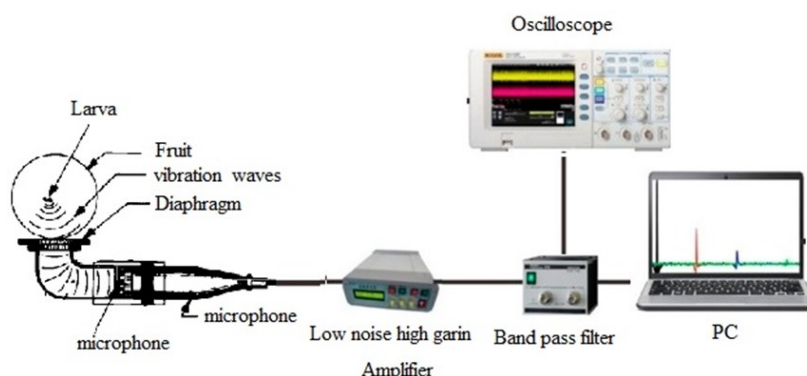

Figure 6. Diagram of acoustic system for detecting insect infestation in fruit. Source: Webb et al. 1988.

(Hagstrum et al. 1996; Shuman et al. 1993). In another research acoustic sensors such as special probes were inserted into the palm tree trunk in order to record sounds produced by the insect especially in the early stages of its life known as the larval stage where the feeding and other activities of the insect are at their maximum (Al-Manie and Alkanhal 2007). They concluded that once the sound produced by the pest was available through the usage of acoustic sensors and the next step would be to try to find a method for identifying a unique signature of these pests.

4. Gas Chromatography

Gas chromatography (GC) has also been evaluated as a potential technology for detection of hidden insect infestation, owing to the fact that insect herbivory can elicit changes in host plant chemistry and so in volatile emissions (Howe and Jander 2008; Karban and Baldwin 1997; Kendra et al. 2011). It also has been well documented that these chemical changes can occur within host fruit as a result of insect activities (Boevé et al. 1996; Carrasco et al. 2005; Kendra et al. 2011). Preliminary tests by Kendra et al. (2011) indicated that these chemical signals, emitted from fruit with early stages of infestation, were detectable and distinct from that of non-infested citrus (Fig. 7). If insect-infested commodities consistently release unique chemical emissions, this specific signature can provide the basis for advanced pest detection. But, the relatively high amount of time required for each test and also low sensitivity of the method are two main drawbacks, thus further evaluation of the system is needed to apply this technology toward the development of rapid and more sensitive screening methods, e.g. electronic nose.
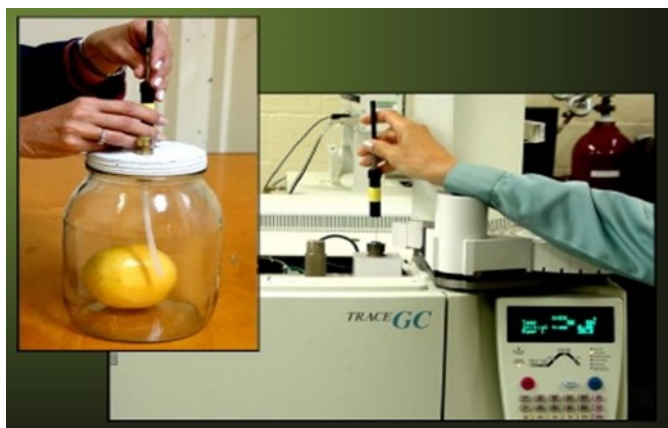

Figure 7. Volatile collections (left) and chemical analysis (right). Source: Kendra et al. 2011.

5. Conclusions

The present paper reviews and summarizes the non-invasive techniques that have been used for insect infestation detection in fruits and vegetables, and also discusses main merits and drawbacks of these techniques for real-time monitoring in industrial applications. Most of the methods for non-invasive monitoring of insect infestation in fruit are based on spectroscopic and imaging techniques including fluorescence spectroscopy, visible-IR spectroscopy, and hyperspectral imaging, x-ray imaging, thermal imaging and MRI. But acoustic method and chemical emission detection have also emerged with considerable promise. Some of the challenges in these techniques are: (i) the effect of background data in the resulting profile or data, (ii) optimization of the technique for a specific fruit and insect and (iii) automation of the technique for continuous automated monitoring of insect infestation under real conditions. In order to achieve high accuracy using these techniques, there is a need for each specific fruit and insect to be assessed by a technique based on their characteristic. Furthermore, different methods could be integrated and used simultaneously for reliable and real-time monitoring to achieve higher insect infection detection and management.

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