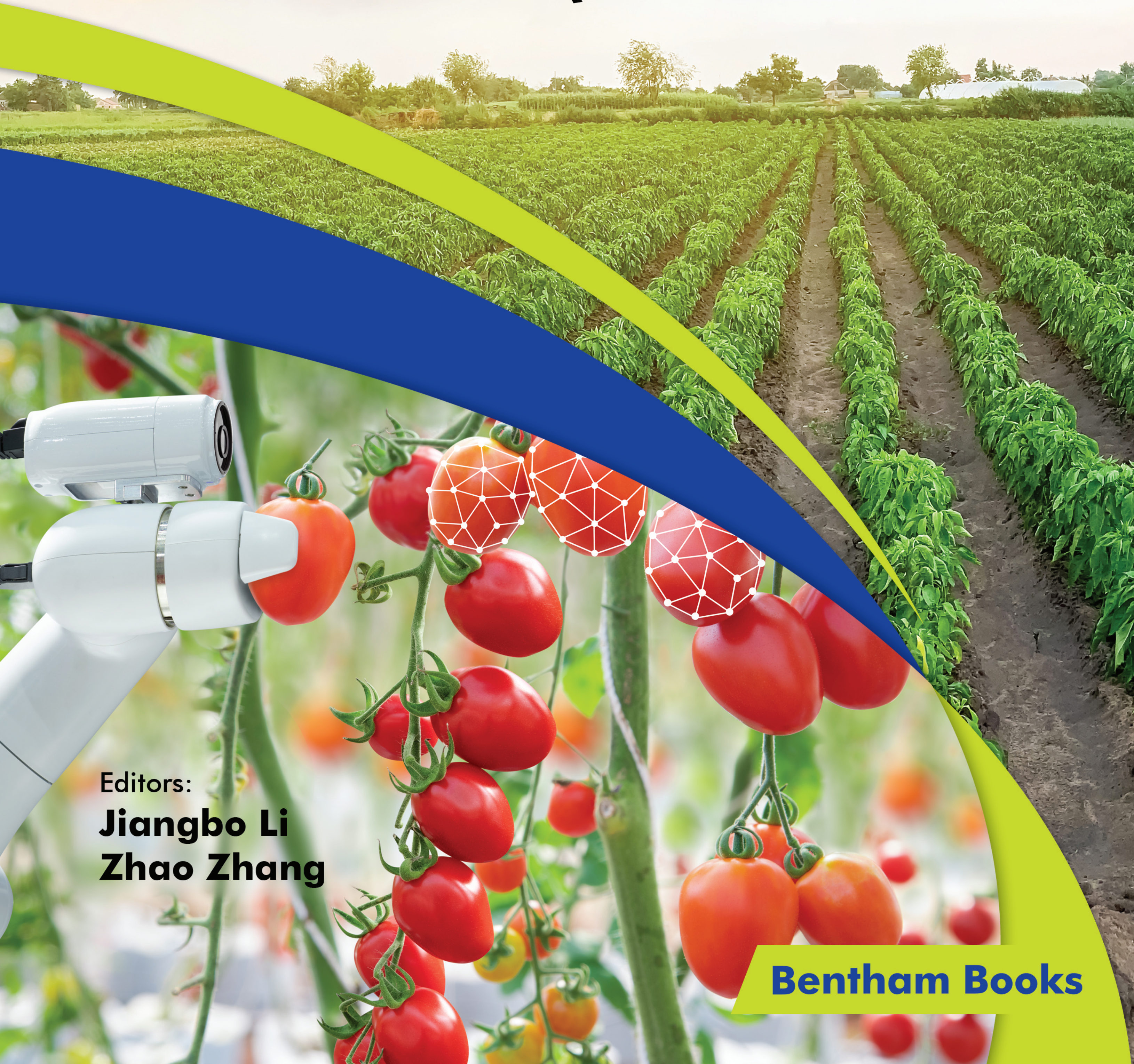
NONDESTRUCTIVE EVALUATION OF AGRO-PRODUCTS BY INTELLIGENT SENSING TECHNIQUES



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PREFACE

With rapid progress in both theory and practical applications, Artificial Intelligence (AI) is transforming every aspect of life and leading the world to a sustainable future. AI technology is fundamentally and radically affecting agriculture in a positive manner to convert it to be smart – improved efficiency, reduced environmental pollutions, and enhanced productivity.

With such rapid progress in AI transforming the agriculture era, it is appropriate timing to publish a relevant book to update the progress to an academic and industrial domain, which inspires the generation of this book titled *Nondestructive Evaluation of Agro-products by Intelligent Sensing Techniques.* This book focuses on intelligent sensing techniques in the nondestructive evaluation of agro-products and describes existing and innovative techniques that could be or have been applied to agro-products' quality and safety evaluation, processing, harvest, traceability, *etc*.

The book includes 11 individual chapters, with each chapter focusing on a specific topic. Chapter 1 introduces representative techniques and methods for nondestructive evaluation, Chapters 2, 3, 5, 6 and 7 present quality evaluation of agro-products (*e.g.*, fruits, vegetables and meat) based on intelligent sensing technologies, including machine vision, near-infrared spectroscopy, hyperspectral/multispectral imaging, bio-sensing, multi-technology fusion detection, *etc*. Chapter 8 describes intelligent sensing technologies for the processing of agro-products, and Chapters 4 and 9 mainly introduce the grading system and traceability of agricultural products, followed by Chapter 10 on the agricultural products harvest platforms. In addition, Chapter 11 on using unmanned aerial vehicles for crop information extraction expands the topic to field crops, which reflects the future trend.

As a professional book in the subject area, *Nondestructive Evaluation of Agro-products by Intelligent Sensing Techniques.* is written by the most active peers in this field from a number of countries, which significantly highlights the international nature of the work. Through the introduction of methods, systems and applications, this book enables readers to systematically understand the intelligent sensing technologies of nondestructive evaluation of agro-products. This book can also be used as a reference for researchers and managers in the field of nondestructive evaluation of agro-products and food.

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CHAPTER 1

Representative Techniques and Methods for Nondestructive Evaluation of Agro-products

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Abstract: Property, quality and safety assessment of agro-products are increasingly gaining attention due to the potential human health concern as well as social sustainable development. Emerging techniques and methods have particular advantages in nondestructive evaluation of agro-products due to their simplicity and faster response time, and reliable results, compared with the conventional visual inspection and destructive methods. This chapter briefly elaborates the principles and system components of some representative techniques, in particular, near infrared spectroscopy, infrared spectroscopy, fluorescence spectroscopy, Raman spectroscopy, laser induced breakdown spectroscopy, traditional machine vision, hyperspectral and multispectral imaging, magnetic resonance imaging, X-ray imaging, thermal imaging, light backscattering imaging, electrical nose and acoustics. The recent applications and technical challenges for these representative techniques are also presented.

Keywords: Agro-products, Methods, Nondestructive Evaluation, Techniques.

1. INTRODUCTION

Agro-products, like fruits, vegetables, and meat, are a major category of food products in the human diet. They contain essential nutrients, such as carbohydrates, fats, proteins, vitamins, and minerals. Property, quality and safety evaluation of agro-products, which directly relates to human health and the sustainable development of a country, has received increasing emphasis from government and has attracted great social concern and global attention. A considerable amount of effort has been made in developing techniques and methods to inspect and evaluate the property, quality and safety of agro-products. Conventional evaluation methods are commonly conducted through instrumental

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analytical measurements, which can be stationary or hand-held but mostly off-line subjective and destructive in nature [1]. Therefore, there is an increasing demand for nondestructive evaluation of agro-products, because of the importance of determining the optimum time for harvest, monitoring the changes of chemical compositions and structured properties for postharvest, and grading quality and safety of individual pieces of agro-products at the packinghouse.

In recent decades, different nondestructive techniques based on different principles, procedures, and/or instruments, such as vision, spectroscopy, spectral imaging, acoustics, biosensing, and electrical nose/tongue, have been investigated and/or developed for the evaluation of agro-products, including chemical composition, physical structure, mechanical property, and food hazard. Unlike conventional methods, these emerging techniques and methods acquire data without contact with samples, thus providing nondestructive measurements. Generally, nondestructive testing is the evaluation performed on any agro-product, for example, an apple, without changing or altering the sample in any way, in order to determine the absence or presence of conditions that may have an effect on certain characteristics (*e.g.*, quality attributes) [2].

This chapter reviews the representative techniques and methods for nondestructive evaluation of agro-products, including near infrared spectroscopy, infrared spectroscopy, fluorescence spectroscopy, Raman spectroscopy, laser induced breakdown spectroscopy, traditional machine vision, hyperspectral and multispectral imaging, magnetic resonance imaging, X-ray imaging, thermal imaging, light backscattering imaging, electrical nose, acoustics, and other potential techniques. It provides an overview of basic principles, typical system components, and/or popular applications of these nondestructive techniques for evaluating the property, quality and safety of agro-products. A short discussion on the technical challenges and future outlook for these representative nondestructive techniques is also given.

2. EMERGING NONDESTRUCTIVE TECHNIQUES

2.1. Near Infrared Spectroscopy

Near infrared (NIR) spectroscopy is a common and useful nondestructive technique for agricultural product evaluation, which has the advantages of rapid and no sample pretreatment. It has been used for the quality detection of agricultural products such as soluble solid contents in fruit [3], starch in wheat [4], fatty acid in milk [5] and so on. The basic principle of NIR spectroscopy is that when a beam of NIR light illuminates a certain agricultural product, the irradiated agricultural product will selectively absorb light of certain frequencies, thereby generating an NIR absorption spectrum. And the NIR spectrum mainly contains the information of overtone and combination absorption of hydrogen groups (C-H, O-H, N-H), which is related to the quality parameters of agricultural products. Therefore, by establishing the mathematical relationship between the spectral information and the quality of agricultural products, we can detect the quality of agricultural products rapidly and nondestructively. The wavelength range of NIR is 780-2500 nm, which can be divided into short wave NIR (780-1100 nm) and long wave NIR (1100-2500 nm). Sometimes, the visible band is used together with near infrared, and it is called visible/near infrared (Vis/NIR) spectroscopy. Generally, the NIR technique has two modes: reflectance (Fig. **1a**) and transmittance (Fig. **1b**). Liquid samples adopt the transmittance mode; for solid samples, the reflectance mode is usually used in the long wave near infrared region, while the transmittance mode can also be chosen in the short wave near infrared region due to its strong penetration ability.

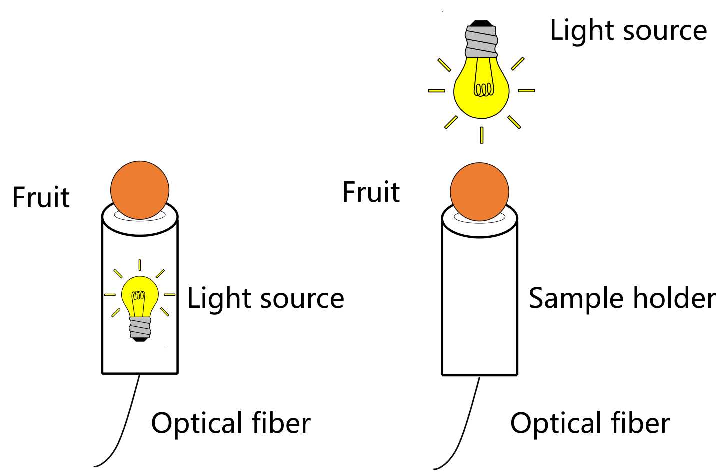

Fig. (1). Two detection modes of Vis/NIR for Nanfeng mandarin fruit: **(a)** reflectance; **(b)** transmittance.

At present, various spectrometers are available and used for NIR spectroscopy. According to different spectroscopic principles, NIR spectrometers can be mainly divided into four types, filter type, dispersion type, Fourier transform and acousto-optic tunable filter. A detector is an important part of the NIR spectrometer, whose function is to transform the optical signal into an electrical signal. In addition, the wavelength range of the NIR spectrometer is also determined by the photosensitive element material used in the detector. The materials of photosensitive elements mainly include Si, Ge, PbS, InSb, InGaAs, *etc.* Halogen tungsten lamps are generally used in NIR spectroscopy as light source, and sometimes light emitting diode (LED) is also used.

CHAPTER 2

Evaluation of Quality of Agro-Products by Imaging and Spectroscopy

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Abstract: The quality of agro-products is the foremost current issue for the food industry and consumers. Healthful agro-products such as fruits and vegetables, meat, grains, and dairy products are essential for human life, and reliable quality evaluation is important for product safety and consumer appeal. As a result, rapid and precise evaluation methods for the quality of agro-products are required. In this regard, optical sensing techniques such as imaging and spectroscopy are among the most promising techniques currently investigated for quality assessment purposes in agricultural fields. This chapter aims to present the basic concepts, components and principles of imaging and spectroscopy techniques in a comparative manner for agriculture application. Moreover, this chapter also elaborates upon the partiality of the optical sensing techniques by highlighting previous studies in agricultural applications. The insights in this chapter will help a novice to understand and encourage further knowledge about optical sensing techniques.

Keywords: Agro-product, Hyperspectral imaging, Imaging, Spectroscopy.

1. INTRODUCTION

The quality of agro-products is affected by a variety of factors which, aside from those factors that are also related to food safety problems, may be weighted or flexible depending on customer awareness and current market conditions. Furthermore, agro-products have sample variations among batches or individual units, even when assessing the same product or cultivar type. Thus, evaluation of the quality of agro-products is more difficult than that for industrial products and needs a more sophisticated sensing technique. New developments in sensing

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devices have allowed us to open a world of novel inspection methods. Optical instruments are a prominent example of advanced technologies used for food quality, including techniques such as imaging, spectroscopy, and hyperspectral imaging. In contrast with traditional methods for evaluating food and agro-products, these rapid techniques can deal with high throughput inspection. It is very important to quickly assess the external and internal attributes of agro-products in the product pipeline since those attributes are directly associated with both manufacturer profits and customer safety [1]. As a result, a wide range of evaluation techniques for agro-products has been suggested for assessing appearance, texture and chemical components on agro-products. This chapter targets understanding of the basic principles and concepts of optical techniques, especially spectroscopy and imaging, and also broadly presents their application for the assessment of agro-products in different parts of the world. The discussion presents information about the application of optical technologies for the quality evaluation of agro-products categorized according to major agricultural products.

2. SPECTROSCOPY TECHNIQUES

A good way to work with agro-products, determine them or define their attributes is to see how light interacts with them. Spectroscopy techniques are based on the interaction of light with matter and examine how light behaves in the target. Seeing how light interacts with agro-products is a good way to characterize or define some of their various qualities attributes. A spectrum is a measure of the amount of light detected at different wavelengths, showing how much light is reflected, absorbed, or transmitted from the target. Spectral data acquired through spectroscopy techniques can be interpreted as fingerprints for recognizing different materials based on their different spectral signatures. Conversely, these spectral signatures can be identified from the spectrum of the target. Therefore, spectroscopy techniques enable us to measure properties that are invisible to the human eye. In the agricultural field, the spectroscopy techniques are generally used to evaluate qualities that cannot be visually determined by the eye, such as the pigment content and soluble solids content of apples, mango maturity, or water content perdition of grape leaves [2 - 5]. Techniques using ultraviolet-visible (UV-VIS), fluorescence, infrared (IR), and Raman spectroscopy are usually adopted in the agriculture field. For evaluating the quality of agro-products, the technique selected is dependent on the target material and the attributes of interest, since spectroscopy techniques differ in their principles and effectiveness with various chemical substances.

2.1. Types of Spectroscopy

Ultraviolet-Visible (UV-VIS) spectroscopy is called absorption spectroscopy or reflectance spectroscopy and can measure wavelengths of light ranging from 100 nm to 380 nm (UV) and from 380 nm to 750 nm (VIS). The light absorption or reflectance in the visible range is related to the color of the chemicals involved. Fluorescence spectroscopy is complementary to absorption spectroscopy. Fluorescence deals with transitions from the excited state of a system to the ground state of the system, while absorption deals with transitions from the ground state to the excited state. Fluorescence spectroscopy is distinguished from other spectroscopy by the emission of light from the targeted substance material. When some energy from the incident light (excitation) is absorbed by the substance, the substance radiates light (emission) at typically lower energy. This emission of light is called fluorescence. Fluorescence spectroscopy is commonly used for food analysis due to the high sensitivity and selectivity of fluorescence measurements in food materials. Infrared (IR) spectroscopy is performed at IR wavelengths from 780 nm to 1 mm. In general, subdivisions of this spectral region are often described using the following scheme: near-infrared (NIR), short-wavelength infrared (SWIR), mid-wavelength infrared (MWIR), long-wavelength infrared (LWIR) and far infrared. Sometimes, NIR and SWIR are known as reflected infrared, while MWIR and LWIR are called thermal infrared. As the full scope of IR spectroscopy and its applications are so voluminous as to merit its own book, this chapter will only discuss IR spectroscopy and imaging in terms of NIR and SWIR techniques, which are popularly used for applications in agriculture. Raman spectroscopy is a light scattering technique, whereby molecules in a substance scatter incident light from a high intensity laser light source. Most of the scattered light-called Rayleigh scattering-occurs at the same wavelength as the laser source, but does not provide meaningful information. On the other hand, a small amount of the scattered light-called Raman scattering-occurs at various wavelengths different from the laser source, depending on the chemical structure of the analyte.

2.2. Spectroscopy Measurement

UV-VIS spectroscopy can use single-beam or double-beam instruments. In a double-beam instrument, the light is split into two beams, of which one is used for the sample and the other is used for a reference. Photodetectors measure the intensity of both beams, with the reference beam's intensity used to provide a value for 100% transmission, relative to which the sample's absorbance can be calculated. A single-beam instrument performs in a similar way using a single

CHAPTER 3

Evaluation of Quality and Safety of Agro-products Based on Bio-sensing Technique

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Abstract: The quality and safety of agro-products are a global concern due to their significant role in human health and economy, and the detection of hazards or ingredients in agro-products is thus essential to ensure safety. Biosensor, as a newly-emerging but promising detection tool, has contributed a lot in this field. On the one hand, based on the high sensitivity and specificity of bio-receptors for target capture and the diversity of transducers for signal transduction, biosensors exhibit capabilities for highly sensitive, specific, accurate and rapid detection. On the other hand, the combination/integration with miniaturized and portable platforms/devices endows biosensors with unrivaled advantages in low-cost, in-field and nondestructive detection. This chapter gives a systematical introduction of biosensors for the evaluation of quality and safety of agro-products, emphasizing on new biosensing principles and the advantages of exceptional analytical performance for rapid and in-field evaluation. Recent advances in biosensors for the detection of pesticide residues, antibiotic residues, pathogenic bacteria and mycotoxins, heavy metal ions, food allergens, and ingredients in agro-products are surveyed (mainly in 2018-2020).

Keywords: Agro-product, Allergen, Antibiotic, Biosensor, Food, Heavy metal ion, Mycotoxin, Nanotechnology, Nondestructive detection, Pathogenic bacteria, Pesticide.

1. BRIEF INTRODUCTION OF BIO-SENSING TECHNIQUE FOR THE EVALUATION OF QUALITY AND SAFETY OF AGRO-PRODUCTS

Agro-product is one of the most important necessities for human survival and health. However, the safety of agro-product has been broadly threatened by microbial contamination, pesticides and antibiotic residues, heavy metal ions, spoilage and adulteration. Therefore, strict evaluation of the quality and safety of agro-product has long been regarded as one of the most important issues to ensure the safety of the whole production and supply processes. For effective evaluation,

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the following concerns have to be addressed. (1) The low concentration but high toxicity of hazards in agro-product requires the evaluation to be highly sensitive. (2) Complex ingredients and a variety of homologous hazards in agro-products highlight the significance of specific and accurate identification and quantitation of target against diverse interferences. (3) Low-cost, user-friendly and portable detection devices are preferred since agricultural products are relatively cheap while the detection is generally completed by workers without professional skills in the field. (4) Smart detection has attracted increasing attention due to the strong trend to integrate the detection results with the informatics system. (5) Additionally, non-destructive detection is also in demand since it not only benefits fast analysis without time-consuming and complex sample pretreatment but also maintains the intact state of agro-products for follow-up growth or sale.

The above concerns have flourished the development of a wide range of evaluation techniques for the quality and safety of agro-products, such as traditional plate counting, high-performance liquid chromatography (HPLC), gas chromatography, mass spectrometer, *etc.* They have contributed to high sensitivity, accuracy and sample throughput but still suffer from some disadvantages, including complicated pretreatment and tedious analytical procedures, the requirement of sophisticated and expensive instruments, highly trained personnel, as well as controlled lab atmosphere. Therefore, their practical and broader applications are rather limited. It always remains a strong impetus to develop rapid, sensitive and portable detection tools.

Biosensors are defined as analytical devices incorporating a biological material, a biologically derived or a biomimetic material (termed as a bio-receptor), intimately associated with or integrated within a physicochemical transducer or transducing microsystem (termed as a transducer) [1, 2]. The bio-receptor can be an enzyme, antibody (Ab), nucleic acid (both DNA and RNA), tissue, cell, molecularly imprinted polymer (MIP), *etc.* General signals (transducers) include electrochemical (EC), optical, gassy, piezoelectric, magnetic, thermal signal and so on [2]. The bio-receptor recognizes the target and the transducer converts the recognition event into a readable signal that is proportional to the amount/concentration of the target (Fig. **1**). Since the birth of the first biosensor (enzyme transducer/electrode) in 1962 [3], biosensors have progressed intensively with interdisciplinary efforts, including biology, engineering, chemistry, electronics, informatics, materials science and nanotechnology. Beyond the well-known glucose biosensor, nowadays, biosensors have been widely applied as powerful analytical tools in a wide range of fields such as biomedical diagnosis, environment monitoring, food safety surveillance, and agricultural applications of growth monitoring, quality analysis and safety detection [1, 4, 5].

Biosensors present the features of high accuracy, sensitivity, specificity, and rapidity. Therefore, they have garnered substantial attention in fulfilling the performance requirement for agro-product evaluation. Meanwhile, due to the characteristics of low cost, ease of fabrication, miniaturization and operation, biosensors have shown great promise in rapid, in-field and nondestructive detection. To date, considerable types of hazards or ingredients in agro-products have been successfully detected *via* various biosensors, ranging from microorganisms (*e.g.* bacteria and viruses) to molecules such as proteins, organic acids, pesticides, antibiotics and toxins. For specific and rapid recognition of targets in complex agro-product samples, a variety of biological or biomimetic materials/entities with remarkable affinities and specificities have been selected or synthesized as bio-receptors for the construction of biosensors, such as Ab, aptamer, enzyme and cell. On the other hand, different transducers have been developed to improve the sensitivity, response speed and portability. EC and optical transducers are two kinds of the most attractive and widely applied transducing techniques for agro-product evaluation by virtue of high sensitivity, rapid response, and significantly, facile demands for instruments and plentiful strategies for signal amplification. EC biosensors are based on electro-analytical chemistry techniques, such as amperometric, voltammetric, impedimetric, and photoelectrochemical measurements. Quantitative sensing is made by varying the electric field and measuring the resulting changes of electrical signals (current, potential, impedance, and *etc.*) as the signal reporter (target/substrate/label) reacts electrochemically on the surface of the working electrode (the transducer) [6]. Optical transduction mechanisms include the change in color, absorbance, fluorescence, luminescence, Raman scattering, plasmon resonance, and so on. These techniques utilize light as the delivery/collection medium to obtain intrinsic information of the physicochemical properties of the optical signal reporter to detect changes/induced changes by the target [7]. Besides, other measurement techniques, such as piezoelectric, magnetic and calorimetric measurements, have also been applied as transducers in biosensors, enriching the evaluation methods for agro-products.

In addition to the performance improvement of biosensors, the demands of in-field evaluation for agro-products have galvanized the development of a series of portable and miniaturized biosensors [8]. The simple constitutions make biosensors powerful candidates for in-field evaluation: biosensors can not only be miniaturized *via* integrating both bio-receptors and transducers on miniaturized systems/devices (*e.g.* chips and flexible polymer substrates), but also be portable, smart and user-friendly *via* applying hand-held readers (*e.g.* smartphone, gas detector and glucose meter) for signal transduction and readout.

CHAPTER 4

Internal Quality Grading Technologies and Applications for Agricultural Products

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Abstract: The internal quality of agricultural products is an important attribute that is considered by consumers when buying them. Grading agricultural products according to their internal quality, is an effective way to make the best use of the products, and thus improve the overall value. In recent years, several nondestructive, intelligent sensing techniques have been studied extensively for detecting the internal quality of agricultural products, including Vis/NIR spectroscopy, multi-/hyper-spectral imaging, nuclear magnetic resonance and imaging, X-ray and computed tomography, electrical nose and acoustic technique. In this chapter, the working principle of each technique is provided, and corresponding applications in the agricultural domain are reviewed to provide overall understanding of these techniques. The challenges and perspectives of these techniques are also analyzed.

1. INTRODUCTION

With the improvement of living standards of human beings in recent decades, the quality of agricultural products has become a key factor that consumers would consider when buying them [1]. Quality is not a single well-defined attribute and is often evaluated or represented by several attributes, including color, shape, texture, defects, sugar content, firmness, soluble solids content (SSC), acidity and nutritional contents [2]. These attributes can be grouped into two categories, external and internal quality.

Recent developed nondestructive, intelligent sensing techniques have been studied extensively for the quality detection of agricultural products, both externally and internally. However, due to the difference in detecting mechanisms of different

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sensing techniques, some of them are unable to acquire the quality information deep inside the tissue, therefore they can only be used for external quality detection, such as machine vision, while others can acquire the internal information of agricultural plant tissue, such as NIR spectroscopy, making them suitable for detecting the internal quality of agricultural products. In this chapter, the techniques that are suitable for internal quality detection of agricultural products including NIR, multi/hyper-spectral imaging, magnetic resonance imaging (MRI), X-ray, computed tomography (CT), electrical nose and acoustic technique, are reviewed, as well as applications and challenges.

2. INTERNAL QUALITY GRADING TECHNOLOGIES AND APPLICATIONS

2.1. Vis/NIR Spectroscopy

2.1.1. Principle

Vis/NIR spectroscopy is a type of vibrational spectroscopy that covers the range of the electromagnetic spectrum between 380 and 2500 nm. This region can be further divided into three parts: visible (380-780 nm), shortwave near-infrared (780-1100 nm), and longwave near-infrared (1100-2500 nm). When incident light hits a sample, the visible and near-infrared photons penetrate and interact with the biological materials. The photons in the visible region are mainly absorbed by pigments (carotenoid, anthocyanin, and chlorophyll), while the near-infrared photons have strong interactions with hydrogen bonds such as N-H, C-H and O-H [3, 4]. During the interaction with biological materials, the photons may be absorbed or scattered, resulting in reflected or transmitted light exiting from the sample that carries its internal chemical and structural information (Fig. **1**). The reflected or transmitted light is dispersed by monochromators and then received by detectors, forming the Vis/NIR spectra, which can be used for sample internal quality analysis [1].

When detecting the internal quality of agricultural products, a Vis/NIS system is necessary. A typical Vis/NIR system consists of a light source, a spectrometer, a sample compartment, and relevant optics accessories. Based on the arrangement of the detecting system, three detection modes are frequently adopted: reflectance, transmittance, and interactance [1, 5]. In the reflectance mode (Fig. **2a**), the incident light hits a sample and is reflected both diffusely and specularly. The diffuse reflectance interacts with the sample and carries effective information that can be used for internal quality analysis. However, the specular reflectance does not carry useful information about the sample, hence should be avoided [1]. In transmittance mode, it can be further classified as the full transmittance mode (Fig. **2b**) and partial transmittance mode (Fig. **2c**), according to the relative position of the detector and light source. In the full transmittance mode, the light source and detector are configured in the same line at opposite sides of a sample, while in the partial transmittance, the light source, the detector, and the sample are not in the same line. The interactance mode (Fig. **2d**) was first proposed by Conway *et al.* [6] in cases where transmittance and reflectance modes cannot be used directly. The interactance mode is similar to the diffuse reflectance mode. However, there is a light barrier between the detector and light source to block specular reflectance, and the light source is installed parallel to the detector [1].

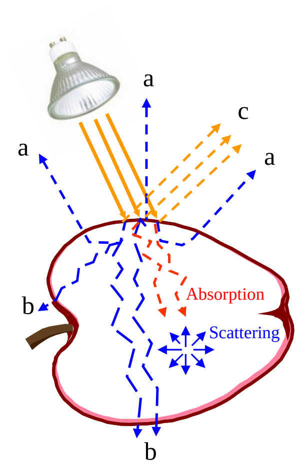

Fig. (1). Distribution of incident light in fruits: **'a'** denotes diffuse reflectance; **'b'** denotes transmittance; **'c'** denotes specular reflectance [1].

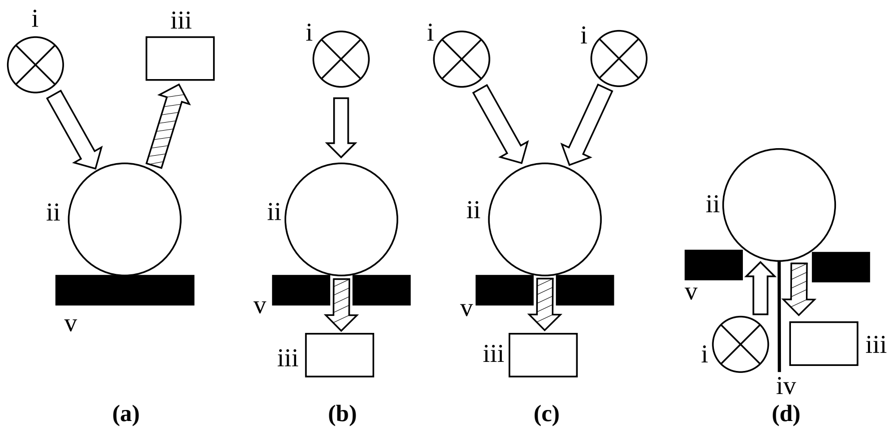

Fig. (2). Detection modes: **(a)** diffuse reflectance, **(b)** full transmittance, **(c)** partial transmittance, and **(d)** interactance, with (i) the light source, (ii) fruit, (iii) monochromator/detector, (iv) light barrier, and (v) support.

CHAPTER 5

Hyperspectral Imaging and Machine Learning for Rapid Assessment of Deoxynivalenol of Barley Kernels

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Abstract: Imaging techniques can be used to evaluate the quality and safety of agricultural products. Fusarium head blight (FHB) results in reduced barley yields and also diminished value of harvested barley. Deoxynivalenol (DON) is a mycotoxin produced by the causal Fusarium species that pose health risks to humans and livestock. DON has currently measured *via* gas chromatography (GC) methods that are time-consuming and expensive. We seek to apply imaging technology to rapidly and non-destructively quantify DON in high throughput and less expensive method. The feasibility of hyperspectral imaging to determine DON contents of barley kernels was evaluated using machine learning algorithms. Partial least square discriminant analysis (PLSDA) was able to discriminate kernels into four separate classes corresponding to their DON levels. Barley kernels could be classified as having low (<5 ppm) or high DON levels, with Matthews's correlation coefficient in cross-validation (M-RCV) of as high as 0.823. PLSR showed good performance in linear algorithms for DON detection, but higher accuracy was obtained by non-linear algorithms, including weighted partial least squares regression (LWPLSR), support vector machine regression (SVMR), and artificial neural network (ANN). Among all algorithms, the non-linear LWPLSR achieved the highest accuracy, with the coefficient of determination in prediction (R^2_P) of 0.728 and root mean square error of prediction (RMSEP) of 3.802. The results demonstrate that hyperspectral imaging and machine learning algorithms have the potential to assist the FHB resistance breeding process by accelerating the quantification of DON in barley samples.

Keywords: Deoxynivalenol, Food safety, Hyperspectral imaging, Machine learning.

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1. INTRODUCTION

Imaging techniques have become valuable tools in the quality and safety assessments of all kinds of agricultural products. The quality and safety of foods are related to their sensorial (such as shape, size, smell, color), chemical compositions (such as protein, starch), and textural (mechanical) properties [1 - 5]. Imaging technologies including color imaging, ultrasound imaging, Raman imaging, thermal imaging, magnetic resonance imaging, X-ray imaging, fluorescence imaging and hyperspectral imaging have been introduced into food research as nondestructive methods [6 - 8]. Each of these imaging modes has its own unique characteristics. For example, color imaging is appropriate for sensing the shape, size or external defect of a specimen at a pixel level [9]. Fluorescence imaging is extensively used to capture the image of fluorescence emission with lower energy from an object excited by higher-energy light [10 - 12]. Among them, hyperspectral imaging records images of continuous spectral bands with high spatial and spectral resolutions [2, 13 - 17]. This technique integrating the characteristics of imaging and spectroscopy is one of the most advanced and widely adopted non-destructive imaging methods for the rapid evaluation of cereal food qualities [18 - 21]. There are three approaches to generate a hyperspectral image, which are point (whiskbroom) scanning, area scanning (tunable filter or staredown), and line (pushbroom) scanning [22, 23]. The point scanning method captures an image point by point, which is not feasible for fast image acquisition [24]. The area scan method can collect images of a fixed scene at different wavebands. The line scan method obtains images of moving samples line by line, which is more suitable for online inspection. Hyperspectral imaging has already been widely used in the quality and safety evaluations of numerous agricultural products, such as pesticide (chlorpyrifos and imidacloprid) prediction in jujube fruit [25], salt stress tolerance assessment in wheat [26], moisture distribution analysis in potato and sweet potato tubers [27], and maturity stage classification in blueberry fruit [2].

Barley (Hordeum vulgare L.) is an important crop for both human and animal consumption worldwide. In the United States (U.S.), barley contributes not only to the domestic food and feed production but also to export markets and trade balance [28]. Fusarium head blight (FHB), caused by a number of different species in the genus Fusarium, is a major disease of barley in many production regions around the world [29]. The infection of Fusarium head blight (FHB) is initiated by airborne spores, which occurs during flowering with warm temperatures and high relative humidity [30]. The initial symptoms appear as water spots on infected spikelets. Then, chlorophyll breaks down and the entire spikelet is bleached. FHB is associated with the production of highly toxic mycotoxins that can significantly impact public health [31]. The yield and quality losses due to FHB are mainly attributed to the accumulation of deoxynivalenol (DON) [32]. DON is a mycotoxin secreted by several Fusarium species to the grain [33]. A positive relationship between FHB severity and DON accumulation has been found, indicating the development of FHB resistant lines with lower DON accumulation is likely [34]. Although crop protection strategies such as crop rotation and fungicide application have been used, the breeding of resistant barley varieties is the most beneficial to reduce FHB severity [35, 36]. Effective resistance breeding requires interdisciplinary research that combines informatics, plant pathology, plant genetics, and years' worth of time. The combinations of different resistance genes can be achieved based on the knowledge of the location and role of each [37]. Currently, a single source of resistance has only partial resistance to FHB, thus breeders continue to combine genes from multiple sources to develop sufficiently resistant cultivars [37]. After new genetic variants are discovered, an important step to obtain high disease-resistant varieties in a breeding program is phenotyping.

Hyperspectral imaging is economical, cost-effective, and non-destructive for determinations of DON in barley, as it does not need additional costs for reagents and the labor compared to conventional chemical methods. This advanced imaging technique obtains full-wavelength spectral images over a wide spectral range and is a very promising way to detect a foreign metabolites produced by a fungus [38 - 40]. The assessment of infected barley has traditionally relied on visual inspection of the disease severity after artificial inoculation [41], which is time-consuming, expensive, and inaccurate. Conventional methods for detecting DON are gas chromatograph-mass spectrometry (GC–MS), and immunological methods such as enzyme-linked immunosorbent assay (ELISA) [6, 42, 43]. However, such approaches require tedious extraction and cleaning steps, and are destructive. In addition, it takes a long time to get the results, and the analysis of the sample is expensive. A more effective means to screen for disease resistance would be simple and rapid. Grain buyers/processors and breeders need such a technique to enhance the detection efficiency for DON content in barley grain. To avoid health risks, it is important to have an effective automated method to assay the metabolite. As far as we know, no research has been carried out using hyperspectral techniques to reliably measure DON content of barley samples. Thus, this study will use hyperspectral imaging to detect DON levels of barley grain. The specific objectives of this study were to: (1) build a discrimination method to classify samples of lower DON levels from higher DON levels; (2) evaluate the performance of different linear and non-linear algorithms for quantitative determination of DON contents.

CHAPTER 6

Evaluation of Fungal Contaminants in Agricultural Products by Hyperspectral Imaging

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Abstract: Optical-based technologies offer significant advantages compared with conventional methods for detecting mycotoxin and fungal contamination in agricultural and food commodities, such as rapidness and non-destructiveness. Hyperspectral imaging (HSI) integrates traditional imaging and spectroscopy technologies and thus makes it possible for high-throughput screening analysis in an onsite or on-line manner. Currently, HSI, in tandem with modern chemometrics, has demonstrated interesting and promising results for the detection of mycotoxin and fungal contamination in varieties of agricultural products. Therefore, the objective of this chapter is to give an overview of current research advances of HSI in both fluorescence and reflectance modes for the evaluation of mycotoxin and fungal contamination in agricultural and food commodities. Advances of HSI in evaluation of the main mycotoxins, including aflatoxins, ochratoxins, deoxynivalenol, fumonisins and their related fungal contaminants, are reviewed, and the results obtained from different studies are compared and discussed. Perspectives on its future trends and challenges concerning mycotoxin and fungal evaluation are also addressed.

Keywords: Chemometrics, Fluorescence, Fungus, Hyperspectral imaging, Mycotoxin, Rapid and nondestructive detection, Reflectance.

1. INTRODUCTION

1.1. Major Fungal Contaminants in Agricultural Products

Mycotoxins are toxic secondary metabolites mainly produced by different fungal species such as *Aspergillus* (*A.*), *Penicillium* (*P.*) and *Fusarium* (*F.*) [1]. Mycotoxin contamination frequently occurs in various food and feed commodities, leading to human and animal health risks at the global level. If ingested, mycotoxins may cause acute or chronic disease episodes, with carcino-

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genic, mutagenic, teratogenic, estrogenic, hemorrhagic, nephrotoxic, hepatotoxic, neurotoxic and/or immunosuppressive effects [2]. To date, hundreds of mycotoxins have already been identified, but the most important ones regarding their prevalence in contaminated agricultural products are aflatoxins (AFs), ochratoxins (OTs), deoxynivalenol (DON), fumonisins (FMs), zearalenone (ZEN) and patulin [1]. Some of these have been classified by the world health organization (WHO) as human carcinogens. For instance, AFs are identified as human carcinogens (Group 1); OTs and FMs are classified as possible human carcinogens (Group 2B) [3]. The chemical structures of these main mycotoxins can be found in the study by Agriopoulou *et al*. [4].

AFs are among the most poisonous mycotoxins and are produced by certain fungi of the genus *Aspergillus*, predominantly *A. flavus* and *A. parasiticus* [5]. Among the 18 identified types of AFs, the naturally occurring and well-known types are aflatoxin B_1 (AFB_1), aflatoxin B_2 (AFB_2), aflatoxin G_1 (AFG_1) and aflatoxin G_2 (AFG_2) [6]. AFs are mycotoxins largely related to agricultural products produced in the tropics and subtropics under humid climate, such as cereals, oilseeds, spices and tree nuts. Contamination with AFs can occur both pre-harvest and post-harvest. OTs are primarily produced by *Aspergillus* and *Penicillium* species [7]. OTs may contaminate cereals (barley, corn, oats, rice, rye, wheat) and other plant products (coffee beans, nuts, dried peanuts, spices, dried fruits, raisins, wine, grape juice, and beer). Among all the OTs, Ochratoxin A (OTA) is the most prevalent and toxic [8]. DON is a toxic fungal metabolite primarily produced by *F. graminearum* and *F. culmorum* common in grains, such as wheat and wheat-based products. DON is also known as vomitoxin due to its strong emetic effects after consumption [9]. FMs are mycotoxins produced in cereals by pathogenic fungi, namely *F. verticillioides, F. proliferatum*, and related species [10]. Moreover, *A. nigri* also produces FMs in peanut, corn and grape plants [11 - 15]. Corn and corn-based products are most commonly infected with FMs, however, their presence also appears in several other grains (rice, wheat, barley, corn, rye, oat and millet) and grain products [16, 17]. More than 15 fumonisin homologues are known and characterized as fumonisin A, B, C, and P [18, 19]. Further, among fumonisin B (FB), FB_1, FB_2, and FB_3 are most abundant, with FB_1 being the most toxic form.

The toxicity of these mycotoxins has led many countries to set up strict regulations for their control in food and feed and the consequent establishment of legislation to control their possible contamination [20]. Effective analytical methods play a key role in reducing the risk of mycotoxin contamination in the food and feed chains. The traditional culture method and microscopic identification of fungal infections, is a tedious and time-consuming process requiring a significant amount of expertise. Conventional analytical methods for mycotoxins include thin-layer chromatography (TLC), high-performance liquid chromatography (HPLC), gas chromatography (GC), capillary electrophoresis (CE) and immunoassay-based technique like enzyme-linked immunosorbent assay (ELISA) [2, 21, 22]. Determination of mycotoxins using these methods is generally a long process which involves extraction procedures using solvents and an identification process based upon chromatographic or immuno-techniques. In addition, the uneven presence of mycotoxins in large-scale products often causes the traditional sample-based analyses to present a limited view of the degree of contamination, *i.e.*, they are subject to sampling error. Therefore, there is a great need for a more rapid technique for high-throughput detection of fungal infection and mycotoxins in agricultural and food commodities in a nondestructive manner, before they enter the supply chain.

Among currently emerging technologies, the optical-based methods have been demonstrated to have great potential for rapid and nondestructive determination of various quality and safety attributes of agricultural and food commodities. As one of the promising optical detection technologies in agriculture, hyperspectral imaging (HSI) technology has provided interesting and encouraging results for the detection of mycotoxin and fungal contamination in varieties of agricultural products. Therefore, the main goal of this chapter is to give an overview of the current research progress in the application of HSI technique for rapid and nondestructive evaluation of mycotoxin and fungal contaminants in different agricultural products. Specifically, applications of both fluorescence and reflectance HSI in the detection of the main mycotoxin contamination, including AFs, OTA, DON, FMs and their related fungal infection, are covered in this chapter. Perspectives of its future trends and challenges concerning mycotoxin and fungal contamination evaluation are also discussed.

1.2. HSI Technology

In the past two decades, HSI technology has seen a significant increase in agricultural and food research applications. By integrating conventional imaging and spectroscopy technologies for data acquisition, HSI technology can produce three-dimensional (3D) hyperspectral images with two spatial dimensions and one spectral dimension. Therefore, HSI makes it possible to obtain the spectral information at each pixel of a hyperspectral image, and also the image information at each covered wavelength. There are three main approaches used for 3D hyperspectral image acquisition. One approach is a point-based method which involves recording spectrum of pixel one at a time until all pixels in an image are accounted for. This approach generally uses a spectrometer and linearly moves the fiber optic head across the target area for data acquisition and the hyperspectral image data are accumulated pixel by pixel. Another approach

CHAPTER 7

Intelligent Sensing Technology for Processing of Agro-products

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Abstract: Intelligent sensing technology of agricultural products can effectively guarantee food quality and safety, and is the key technical support to promote the rapid development of the world's agricultural products processing industry, bringing more opportunities and development space to the emerging agricultural products processing industry. Intelligent sensing technology for agricultural products is a multidisciplinary research field, which has the advantages of fast detection speed, convenient operation, and easy online detection. This work reviews the research of optical, acoustic, electrical, magnetic, and bionic sensing technologies in the processing of agricultural products, expounds the principle, structure, and typical applications of each sensing technology, and summarizes the problems and trends in the development of each sensing technology. Intelligent sensing technology for agricultural product quality and safety is developing towards the direction of high sensitivity, automation, networking, intelligence, and multi-function, and has gradually become an indispensable and important technical means for agricultural product quality and safety inspection. The intelligent sensing technology of agricultural products is developing synchronously with the integration of the Internet of things, big data, and cloud computing, which can realize the standardization, refinement, and intelligent management of the agricultural products processing process.

Keywords: Acoustic sensor, Agricultural processing, Analog sensory, Electrical sensor, Intelligent sensing, Magnetic sensor, Optical sensor.

1. INTRODUCTION

The processing of agricultural products is an important link of agricultural industrialization, which improves the rate of conversion of agricultural products, the key to realize value-added processing, to accelerate the development of modern agriculture in the world. Agricultural and food products with high quality

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and safety are essential parameters for the consumers, and it is important to develop a compulsory examination of agricultural products and processed products [1 - 3]. Intelligent sensing technologies of the processing of agricultural products are the critical support for the healthy and rapid development of the world agricultural industry in the new era. A new round of scientific and technological revolution will bring subversive changes to the agricultural products processing and manufacturing industry, and will also bring more opportunities and development space to the emerging agricultural products industry [4, 5]. Some of the technological advancements being employed and currently in progress in the field of agricultural products processing and manufacturing include high-end processing and manufacturing equipments, sensors that simulate human senses like electronic sensors for collection of internal and external information; intelligent sensors that mimic the human brain and nervous system functions from external feeling to transmission of signals to the brain, and also give connotation of multiple sensing levels and degrees; and smart sensors used for monitoring agricultural products. Intelligent sensing technologies of agricultural products can effectively guarantee the quality and safety of food and will become the mainstream of the future development of the agricultural products processing industry.

Food quality and safety is a complex issue in the context of the internationalization of agricultural production and economic globalization [6]. Researchers focus on the research and development of agricultural product intelligent detection and processing technology and equipment, study the cutting-edge scientific issues of agricultural product processing technology, and respond to the new challenges of the scientific and technological revolution of the agricultural product processing industry by carrying out high-level, substantive and sustainable scientific and technological breakthroughs.

Intelligent sensing technology for agricultural products is multidisciplinary, involving computer technology, information technology, sensor technology, image processing, spectral technology, applied mathematics, pattern recognition, and other knowledge in a number of disciplines [7 - 10]. Agricultural intelligent sensing technologies which utilize sound, light, and magnetic field in their operation can acquire a lot of information that reflects the kind of investigated properties of the product under analysis. These sensing technologies have the advantages of rapidness, ease of operation and online testing [11].

It is one of the hotspots in the research of the current agricultural products processing. The traditional wet chemical method is generally handling destructive test samples, although the detection result is of high precision, but the method is high consumption, excessive complexity, and time delay. Meanwhile, the analytical process using chemical agents will produce waste gas and liquid leading to environmental pollution. Compared with the wet chemical analysis method, the intelligent sensing technology can be efficiently used as a fast, accurate and cost-effective way to indicate the quality and safety [12]. Intelligent sensing technology is developing towards the direction of high sensitivity, automation, network, intelligence and multi-function, and gradually becomes an indispensable and important technical means of agricultural product quality and safety detection, which is complementary to the detection of large and precise physical and chemical analysis instruments.

Agricultural products intelligent sensing technology is developed synchronously with the integration of the internet of things, big data and cloud computing, which can realize the standardization, refinement and intelligent management of agricultural products processing. This chapter summarizes the principles and characteristics of optical, acoustic, electrical, magnetic and analog sensory sensing technology, analyses the research status of sensing technology in agricultural product processing, and introduces typical application cases, points out the problems of sensing technology in agricultural product processing, and its application prospect.

2. OPTICAL SENSING TECHNOLOGY IN AGRICULTURAL PRODUCTS PROCESSING

2.1. Principle of Optical Sensing Technology

Optical sensor technology is mainly based on the principle of interaction between light and matter. When light is incident from one medium to another, due to the different refractive index of the medium, the propagation speed of light will change, which causes the change of the propagation direction of light, which is the refraction phenomenon of light. Fig. (**1**) shows the electromagnetic spectrum range used in agricultural processing.

The biological tissue of agricultural products is composed of cells of different sizes, densities and components, which are opaque, turbid and highly scattering in microcosmic. When light is transmitted in tissue, it interacts with the tissue in a variety of ways, as shown in Fig. (**2**). Wherein absorption and scattering will occur simultaneously, and multiple scattering plays a leading role. Photons are usually converted into another form of energy (such as heat energy) after being absorbed, and the transmission direction of photons changes after being scattered, but they will continue to transmit until they are absorbed by the tissue or escape from the surface of the medium. The absorption of light is generated by the transition of molecules from the ground state to high energy level, which is mainly related to the chemical composition of tissues, such as water, sugar, *etc.*

CHAPTER 8

Automation on Fruit and Vegetable Grading System and Traceability

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Abstract: Automated sorting and quality grading of agricultural produce are crucial for providing commodities with consistent quality to the consumers and markets. Machine vision has been playing a key role in this quest by presenting technological solutions that provide robust, consistent, and accurate decisions with minimal human intervention. An end-to-end quality inspection system should recognize the type of agricultural product and then perform quality grading. Accordingly, in this proof-o--concept study, a deep learning-based end-to-end solution for quality inspection of agricultural produce is presented, where an initial system automatically sorts fruits-vegetables, while a second system grades apples by skin quality. Experimental evaluations show that the presented end-to-end solution achieves accurate and promising results, and thus holds high-potential for offering high-impact, traceable and generalizable answers for the industry.

Keywords: Computer vision, Deep learning, Grading, Fruit and vegetable, Machine vision, Quality inspection.

1. INTRODUCTION

Recent advances in the fields of mechanics, optics, electronics, computers, and software have led to the birth of machine vision, an engineering technology proposing high-throughput, integrated mechanical-optical-electronic-software solutions for examining, monitoring and controlling applications [1]. Automated quality inspection of food and agricultural products is one such application where accurate, fast, and objective determination of product quality is required due to high standards of safety and quality expected by the industry [2].

In machine vision-based quality inspection of food and agricultural produce, systems are typically composed of a light source, a device to capture images, and

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an image processing/computer vision-based software to process the images [3 - 6]. Such machine vision systems can be categorized by the technological differences they contain or by the agricultural or food product they are put together for inspection, such as vegetables, grains, fruits, meat, and fish or industrialized products [3].

In the first part of this study, we focused on the machine vision systems dedicated to the inspection of fruit and vegetables. To this end, several solutions have been proposed in the literature [7]. Most of these solutions extract color, texture, and/or shape features from the images [5 - 8] and realize inspection by using a machine learning algorithm such as random forest [8], support vector machines [9], neural networks [10] and the recently popular deep learning [11].

Then, in the following part, we focus on the quality grading of a single type of agricultural product, namely the apple fruit. Quality grading of apple fruits using machine vision is challenging due to numerous apple cultivars existing, various defect types present in the fruit, and the natural variability in its skin color [12]. Many of the machine vision-based apple grading solutions proposed in the literature benefit from different sensing techniques or dedicated lighting/equipment (s) [13 - 16]. Other studies employ ordinary machine vision to automatically grade apples using approaches like thresholding [17], Naive Bayes classifier [18], decision trees [19], support vector machines [20], and neural networks [21].

The recently popular deep learning techniques, which eliminate feature engineering and learn representative features from the data, have dramatically improved the state-of-the-art in several domains [22] including the food industry [23]. However, applications of deep learning in the domains of fruit and vegetable sorting as well as apple grading are still limited. Accordingly, here we propose a deep learning-based automated, end-to-end solution for quality inspection agricultural products, and present a proof-of-concept study where an initial system automatically sorts fruits-vegetables while a second system grades apples by skin quality.

2. METHODS

We propose a deep learning-based automated, end-to-end solution for quality inspection of agricultural produce. The proof-of-concept is presented as a cascaded solution where an initial system automatically sorts fruit and vegetables while a second, subsequent system realizes quality grading of the sorted produce, *i.e.* apple fruits. Details of these two systems will be explained below, and the experimental results obtained will be reported in the following section.

2.1. Automated Fruit-Vegetable Sorting

Initially, we will be addressing the problem of automatically recognizing the type of fruit and vegetable from images by using a deep learning-based system. Below, the image dataset will be introduced first, and then the details of the proposed solution will be explained.

2.1.1. The Supermarket Produce Dataset

In order to evaluate the sorting performance of our proposed deep learning system, we decided to use the Supermarket Produce dataset [24]. The dataset comprises a total of 2633 RGB images from 15 different fruit and vegetable categories - Plum (264), Agata Potato (201), Asterix Potato (182), Cashew (210), Onion (75), Orange (103), Taiti Lime (106), Kiwi (171), Fuji Apple (212), Granny-Smith Apple (155), Watermelon (192), Honeydew Melon (145), Nectarine (247), Williams Pear (159), and Diamond Peach (211) - captured on a clear background at a resolution of 1024x768 pixels. Some example images from the dataset can be seen in Fig. (**1**).

Fig. (1). Example images from the Supermarket Produce dataset.

Previous studies that employed this dataset proposed to use dedicated feature extraction techniques together with machine learning solutions. For example, in a study [24] several color and texture-based features extracted from the images were fed to various conventional classifiers (linear discriminant analysis, support

CHAPTER 9

Robotic Harvesting of Orchard Fruits

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Abstract: Harvesting is one of the most challenging tasks in fruit production. Robotic fruit harvesting technologies are being studied because of labor-intensive and costly handpicking. Due to the unstructured and dynamic characteristics of both the target fruit and its surrounding environment, current harvesting robots have limited performance. Therefore, the commercial applications of most fruit harvesting robots are unrealized. The application and research progress of fruit harvesting robots in apple and kiwifruit harvesting have been reported in this chapter. The applications and development of fruit detection and end-effector design for complex orchard are focused. The main methods used in fruit detection are reviewed, including single feature detection methods, multi-features fusion detection methods, deep learning methods, and 3D reconstruction methods. The technology of end-effector design for selective harvesting with apple and kiwifruit, and shake-and-catch mechanism for bulk harvesting with apple are also reviewed. Existing research problems of fruit harvesting robots in robotic harvesting applications are mentioned, and future development directions of agriculture robots are described.

Keywords: Apple, End-effector, Fruit detection, Kiwifruit, Selective harvesting.

1. INTRODUCTION

The most labor-intensive and time-sensitive task in tree fruit crop production is harvesting. Local growers report that harvesting labor takes about one-third of their annual variable costs, equivalent to the sum of pruning and thinning [1].

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Harvesting is a time-sensitive work in which variable weather patterns can cause uncertainty during employment planning [2]. For example, the threat of an early frost may lead to the demand for fruit picking to surge in the short term. Fruit picking will expose workers to fall hazards and ergonomic injuries by heavy lifting and repeated operations [3]. Therefore, except for the risks associated with labor supply and rising costs, the focus on worker safety has also stimulated interest and research in harvesting mechanization for fruit production. The lack of mechanical harvesting is a serious problem that threatens the long-term sustainability of the fruit tree industry.

To reduce dependence on seasonal labor and harvesting costs, researchers began to devote themselves to the research and development of fruit harvesting robots in the 1980s. Two methods, selective harvesting and bulk harvesting, are used to fully mechanize fruit harvesting [3]. The typical approach for selective harvesting is merging a machine vision system with an end-effector and manipulator to pick a single mature fruit selectively. The typical approach for bulk harvesting is applying vibration to the trunk or branch of the tree with shake-and-catch systems to separate the fruit. Although many attempts have been made in the past thirty years to directly incorporate industrial robot technology in this field-based bio-driven environment, the robotic harvesting system for special crop agriculture has not been commercialized.

The current state of the art robotic harvester is developed for orchard fruits, apples, and kiwifruits that have been trained in modern planning orchards to improve uniformity in size, color, and maturity of fruits on individual trees and across a single varietal block of trees. In modern planning orchards, fruits with simple, narrow, accessible, and productive (SNAP) systems are relatively more convenient to pick compared to apples in traditional orchards [4]. Kiwifruit has been planted on strong supporting structures such as T-bars and pergolas, which is more structured than other fruit trees, and thus easier to perform mechanical operations [5]. Both of them are promising to be harvested robotically in the orchard where significant researches have been conducted.

2. ROBOTIC HARVESTING OF APPLE

To resolve the problem of lack of mechanical harvesting for apples, researchers have proposed two different methods for fully mechanized harvesting of fruit trees [3]. The first method is selective fruit harvesting with robotics technology. Selective fruit harvesting technology aims to use robotic arms in conjunction with sensors to locate apples individually. The second method is bulk harvesting, where vibration is applied to the trunk or branch of the tree to detach the fruits. In all, various technologies such as machine vision, image processing, robot kinematics, sensors, and controls are required to be integrated for robotic harvest systems.

2.1. Fruit Detection for Apple

Apple harvesting robots are required to be able to detect and locate apples in the canopy. However, detecting apples under natural conditions poses complex challenges, including fruit overlap, occlusion, shadows, and bright areas. Numerous researches report that various detection algorithms have been used in apple robot harvesting systems.

2.1.1. Single Feature Detection Methods

Color, shape, and texture are the basic characteristics of fruit detection. The color is one of the most distinctive features used to distinguish between complex natural backgrounds and ripe fruits [6]. In the study of color-based fruit detection and segmentation, image pixels are divided into two categories according to the threshold value, which determines whether the pixel belongs to the background or the fruit object. For alleviating the influence of varying illumination, several color spaces (such as L*a*b*, HIS) are adopted to extract color features [7]. Besides the color feature, studies have also employed shape-based and texture-based detection methods [8], [9]. Fruit detection methods based on extracting geometric features are usually used to detect apple-like spherical fruits. Due to its independent color features, the methods of shape-based analysis are not affected by changes in illuminations. Moreover, images taken under natural orchards have a certain texture difference, which can be used to promote detachment of fruits from the background. Therefore, texture features play a significant role in fruit detection, especially when the fruit is occluded. However, robustness is reduced when detection is based on a single feature, *i.e.*, the method is sensitive to changes in the field environment. Bulanon *et al*. [10] applied a red color difference between the objects to detect apples in different lighting conditions, and obtained a detection rate of 88.0%. Kelman and Linker [11] proposed a localization method based on the convexity of ripe apples in trees, and correctly detected 94% of visible apples. Lv *et al*. [12] used Otsu dynamic threshold segmentation method with color characteristic to segment apple image and detected 86% badly occluded apples. The variable lighting condition in the orchard will affect the intensity of reflected light, while the partial occlusion of fruit by fruits, branches, and leaves will affect the geometric features of fruit in the image. Although the detection method based on a single feature can detect apples in the natural orchard, it cannot completely distinguish between target features. In such a scenario, detection based on a single feature may not be the best approach.

CHAPTER 10

Detection of Wheat Lodging Plots using Indices Derived from Multi-spectral and Visible Images

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Abstract: Lodging is a critical issue in wheat production, resulting in reduced yield, low crop quality, and increased difficulties in the harvest. Wheat lodging detection contributes greatly to crop management and yield estimation, as well as insurance claim issues. The current manual measurement is labor-intensive, inefficient, and subjective. Aiming to develop a more efficient and objective method to distinguish lodging from non-lodging areas, this study collected aerial color and multi-spectral images using drones attached to different cameras. The experimental field consisted of 372 wheat plots of three different sizes and three days' datasets were collected. Individual images were first stitched to obtain an orthomosaic map and then each plot was visually classified as lodging or non-lodging. Features (*i.e.*, color, texture, NDVI, and height) of each plot were extracted. For each day's dataset, 300 plots (~80% of the total plots) were randomly selected to train the Support Vector Machine (SVM) model, while the remaining 72 plots (~20% of the total plots) were used to test the trained model. After training and testing 10 times, the prediction accuracy was obtained by averaging 10 prediction accuracies. When only using one feature to train the model, prediction accuracies ranged from 66% to 86%. The accuracy increased with more features incorporated for model training. When incorporating all four features, the prediction accuracy was about 90%, indicating its desirable performance in distinguishing lodging from non-lodging plots. The model prediction accuracy of using all four features is not significantly different from that of using only two factors (*i.e.*, texture and NDVI). Since data collection and processing workload increased with more features, researchers in the future could specifically focus on extracting and using texture, and NDVI features to train an SVM model for wheat lodging detection, instead of using four features (*i.e.*, color, texture, NDVI, and height).

Keywords: Color, Features, Height, NDVI, Support vector machine, Texture, Wheat lodging.

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1. INTRODUCTION

Following corn and soybean, wheat (*Triticum aestivum* L.) ranks as the third most important crop in the US in terms of production, growing areas, and gross farm receipts [1]. As one of the most important staple crops, wheat is not only a major source of starch and energy in daily foods but also provides several components that are essential and beneficial for health, such as vitamins, dietary fiber, protein, and phytochemicals [2 - 5]. Furthermore, wheat consumption has been demonstrated to be able to reduce the risk of diseases, such as diabetes (type II), cardiovascular disease, and certain types of cancers [6 - 10]. Following Kansas, North Dakota ranks second in wheat production throughout the US, with a yield of 6.5×10^6 MT and $\$1.4 \times 10^9$ economic value in 2017 [11]. However, starting from 2008, the US wheat planted areas and yield continued to decrease due to lower returns and increased competition in the global market [12]. Therefore, there is a need to develop and adopt new technologies to assist with wheat field management to benefit the US wheat industry economically.

Crop lodging, defined as the permanent displacement of stems from an upright position due to external or internal factors, is one of the most critical issues during wheat production in both developed and developing countries [13 - 15]. Wheat lodging can occur either at stem or root [16, 17]. Stem lodging is caused by the bending or breaking of the lower culm internode, while root lodging can be attributed to a failure in root-soil integrity [18, 19]. Lodging can lead to lower yield and poor grain quality, resulting from self-shading, lowered canopy photosynthesis, increased respiration, reduced translocation of nutrients and carbon for grain filling, and high susceptibility to pests and diseases [20, 21]. It has been reported that wheat lodging could reduce yield up to 50% [14, 22 - 25]. In addition, lodging makes the mechanical harvest more difficult, as the low-level wheat spikes are difficult to be pulled into the combine header [26]. Thus, wheat lodging monitoring will contribute significantly to yield prediction, loss evaluation, and harvest strategy planning [27].

A majority of countries have implemented compensatory policies for agricultural losses caused by natural disasters [28 - 31]. In the US, these policies follow the USDA Risk Management Agency, which insures farmers' crops to a certain value of production [32]. While wheat lodging occurs, farmers have to identify the damaged areas by walking into the field and evaluating visually, after which they would submit a written notice of damage within a certain time period (48~72 hrs. from the initial discovery) [33]. Then, the third party of insurance loss adjuster would come to the farm, manually assess the loss, record measurement, and submit a claim, which finally determines whether the farmers would get paid or not [27]. Manual wheat lodging evaluation is laborious, as workers need to walk across a large field area at a high temperature (*e.g.*, 38°C). In addition, the manual approach is so subjective that each individual inspector may come with different conclusions, which may cause disagreement between farmers and representatives of an insurance company. Furthermore, considering error accumulation occurred during the manual measurement using inaccurate tools (*e.g.*, tape and measuring wheel), the calculated results may be significantly different from the real conditions, leading to under or overpayment. Therefore, it is desirable to have an automatic and objective lodging detection method to replace the manual approach.

Remote sensing technology, with a quick development over the past years, provides a potential tool to obtain timely information on crop lodging over large fields [34]. To date, three major technologies have been explored for crop lodging detection, including spectral image-based satellite sensing, radar-based optical sensing, and Unmanned Aerial Vehicles (UAVs) multiple imagery-based sensing [35, 36]. Though the satellite remote sensing covers huge land plots, its performance on lodging evaluation is weak because of limited spatial and temporal resolutions [37]. In addition, spectral differences supposed to be caused by lodging and non-lodging may be contributed by other factors, such as crop stress (*e.g.*, fertilizer, salinity, and drought) and diseases. The radar-based optical sensing has been tested, but its accuracy on lodging monitoring has not been proven [38]. One possible explanation is that radar system-based optical sensing is more suitable for homogeneous and large areas, while lodging usually occurs in a relatively small area [39]. Due to its relatively small area while occurring and high-resolution image requirement for wheat lodging detection, UAVs are considered as a potential tool [34, 40]. Compared to satellite- and radar-based detection method, UAVs have several advantages. On one hand, UAVs can fly relatively low above ground level and instantly capture bird's eye view images with high resolution; on the other hand, a variety of cameras (*e.g.*, thermal, RGB, and multi-spectral) can be customized and attached to UAVs according to different requirements [38]. In addition, with technological advances in computer vision and digital photogrammetry, aerial images can be processed in different approaches, such as producing geo-referred orthomosaic maps and generating digital surface models (DSMs) [41 - 43].

UAVs have been preliminary tested recently in crop lodging detection, such as rice, corn, and canola. For example, Chu *et al*. (2017) [44] used drones attached with RGB and near-infrared cameras for corn lodging severity detection. The collected imagery data was loaded into a photogrammetric software to construct a 3D canopy structure and DSMs, after which the crop height information was used for lodging severity detection. This study confirmed that the 3D model height was significantly correlated with manually measured results (R^2 = 0.88). Li *et al*. (2014) [36] attached an RGB camera to a drone for corn lodging detection [36].

SUBJECT INDEX

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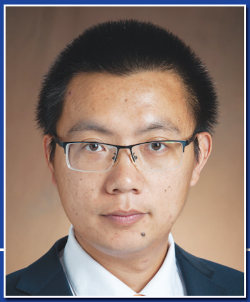
Jiangbo Li

Jiangbo Li received his Ph.D. degree from the College of Biosystems Engineering and Food Science from Zhejiang University. Dr. Li is a researcher at the Research Center of Intelligent Equipment for Agriculture of Beijing Academy of Agriculture and Forestry Sciences. His current areas of research include optical sensing, such as near-infrared spectroscopy, hyperspectral and multispectral imaging techniques and computer vision, all emphasize on solving practical problems in agricultural engineering. Especially, his innovative studies on fruit quality inspection by optical sensing techniques have been widely reported. The results of his work have been published in more than 80 peer-reviewed journal papers.



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Zhao Zhang is a research assistant professor in the Department of Agricultural and Biosystems Engineering, North Dakota State University, Fargo, ND, USA. His major research direction relates to sensing and automation in agriculture, focusing on the application and development of innovative technologies (*e.g.*, UAVs and ground vehicle-based sensors) to support sustainable agriculture. Before joining his current position, Dr. Zhang worked as a postdoc research associate with USDA-ARS Sugarbeet and Bean research unit, which is located in Lansing, MI, USA. During his postdoc, Dr. Zhang developed an apple harvest and infield sorting system that helped him win the 2019 ASABE Rain Bird Engineering Concept. Dr. Zhang earned his Ph.D. degree from Pennsylvania State University, PA, USA, and his Ph.D. project was to develop and optimize an apple harvest-assist unit.