Agriculture Automation and Control

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Fundamentals of Agricultural and Field Robotics

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Agriculture Automation and Control

Series Editor

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The ultimate goal of agricultural research and technology development is to help farmers produce sufficient foods, feeds, fibers, or biofuels while at the same time, minimize the environmental impacts caused by these large scale activities. Automation offers a potential means by which improved productivity, resource optimization, and worker health and safety, can be accomplished. Although research on agricultural automation can be found in the published literature, there lacks a curated source of reference that is devoted to the unique characteristics of the agricultural system. This book series aims to fill the gap by bringing together scientists, engineers, and others working in these areas, and from around the world, to share their success stories and challenges. Individual book volume will have a focused theme and will be guest-edited by researchers/scientists renowned for their work within the respective sub-discipline.

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Preface

Where are We Coming From?

When we joined Washington State University (WSU) around 10 years ago, we were faced with the new form of agriculture that we were not used to. Both of us were trained on mechanization and automation technologies for row crops (such as rice, wheat, corn, and soybean) and most of our career experience was also around the same domain. Dr. Manoj Karkee completed his PhD in agricultural engineering and human computer interaction at Iowa State University working on dynamic systems modeling, control, and navigation/guidance of tractor and towed implement systems. He graduated in 2009 and continued researching more in this area before making the move to Washington. Dr. Qin Zhang graduated with PhD in agricultural Engineering from University of Illinois Urbana-Champaign (UIUC) in agricultural automation and worked at Caterpillar Inc. and UIUC for more than 15 years researching and developing various automation technologies for agriculture, including auto-guidance and intelligent field machinery technologies that have now been widely adopted around the world.

In Washington and the Pacific Northwest (PNW) region of the USA, our work revolves around a completely different farming environment. Contrary to a reasonable level of homogeneity we find in the Midwest in terms of major commercial crops, the PNW region presented one of the most diverse forms of agriculture focusing heavily on high-value fruit and vegetable crops, which are major parts of a cluster of crops called specialty crops. Washington produces more than 300 different commercial crops, presenting unique challenges and opportunities for making farming more efficient and sustainable. Each type of crop is grown in comparatively small acreage. In addition, there are many different crop cultivars and cropping systems planted within a given crop type. Using apples as an example, there are a few dozen different cultivars planted in Washington State alone, and these cultivars are planted in many different crop architectures. In addition to variability in the crop architecture, color, geometric (shape, size), and physiological (e.g., surface toughness) parameters of produce also vary widely. These unique combinations of crop types, cropping systems, and cultivars present unique situations requiring specialized mechanization, automation, and robotic solutions.

Nevertheless, our experience from both row crop and specialty crop agriculture tells us that robotic solutions for all types of agricultural and field applications share a wide range of fundamental theories and principles as well as a fair share of challenges such as difficult field conditions, variable and unstable environment, and biological variability of plant and produce. To address these challenges, as discussed more widely in various chapters of this book, automation and robotics for agricultural and field applications have been in the fore front of research and development in recent years. With the advent of novel, affordable, and more powerful sensing technologies, sensors (e.g., red–green–blue depth) and sensing platforms (e.g., UAVs and ground robots), novel and advanced robotic technologies (e.g., soft robotics), robust machine learning techniques (e.g., deep learning), and increasingly powerful and affordable computational tools (e.g., graphical processing units), we can now envision a world where automating even the most specific/unique field operations (e.g., red raspberry pruning and bundling) is imaginable.

In this context, both public and private (big and small) enterprises around the world are actively involved in research and development of wide variations of robotic technologies for farming and other field applications. As new researchers are attracted to the field every day and as there is an increasing need for training the next generation of workforce for development, operation, and maintenance of smart, robotic technologies for farming and other field applications, a book covering the fundamental principles that can be applicable to a wide swath of applications in various types of agricultural industries was deemed crucial. With this context in the background, this book was conceptualized around 3 years ago, and have been in writing for about 2 years. In this process, we got the full, unconditional support from experts all around the word contributing to the book with their long experience, unparalleled insights, and thoughtful ideas. It was a privilege to read the contributions of 33 professors, researchers, scholars, engineers, scientist, and students from across the globe who are world leaders in their respective fields.

We believe this book fills the gap of a good, comprehensive reference for processors, scientists, engineers, and scholars working actively in robotics, in general, and agricultural and field robotics, in particular. We also believe that this book can provide a great text or primary reference for students who are developing their knowledge and experience in robotics and for early career researchers who are trying to build their research and scholarship programs around agricultural and field robotics. Theories, assumptions, and hypothesis are good starting points and can provide strong motivations. What we just discussed in this paragraph are our assumptions and hypothesis. As we are the scientists who always have doubts on our hypothesis and conduct rigorous research to validate or dis-validate our assumptions and hypothesis, we are now out of control in terms of what we could do differently in the book, and it is up to fellow researchers, engineers, students, and scholars like you to prove us right or wrong in terms of what, if any, values this book brings to you and to the profession.

Organization of the Book

The book has been organized into 3 distinctive parts and 16 chapters. After presenting an introductory discussion on the importance and fundamentals of agricultural and field robotics in Chap. 1, 5 chapters have been presented to describe various sensing and machine vision systems (Part I of the book) as it applies to agricultural and field robotics. Chapter 2 presents color sensing and image processing systems whereas Chap. 3 presents the fundamentals of 3D sensing approaches and systems. Basics on spectral sensing is presented in Chap. 4. Chapters 5 and 6 present various ways crop sensing and scouting can be performed in the field and control environment farming including new research and development efforts in crop phenotyping. Part II of the book, starting with Chap. 7, focuses on mechanisms, dynamics, and control of agricultural and field robotic systems. First, robotic manipulation systems (robotic arms) and their optimization for agricultural applications will be presented in Chap. 7, and end-effector (robotic hand) systems are discussed in Chap. 8. Chapter 9 presents the fundamentals of control techniques with specific focus on robotic harvesting. Chapter 10 presents various aspects of guidance and auto-steering systems whereas Chap. 11 describes technologies for in-field sorting of fruit crops and Chap. 12 presents the basics of modeling and simulation techniques for robotic systems. Third and final part of this book focuses on emerging topics in agricultural and field robotics. In this part, advanced learning and classification techniques (Chap. 13) and digital farming techniques such as the Internet of Things (IoT) and big data (Chap. 14) are discussed. Similarly, two additional emerging topics are covered in Chap. 15 (Human-machine interactions) and Chap. 16 (Plant-machine interactions). All these chapters, generally, begin with fundamental concepts and algorithms followed by specific case studies demonstrating the ways the concepts and algorithms are applied to solve specific agricultural and field robotic challenges. Finally, all chapters present a brief summary and concluding thoughts with authors' insights into the topic area covered.

It is to be noted that this book primarily addresses the fundamentals of agricultural robotics, thus most of the examples, case studies, and cited literature are borrowed from agricultural industries, specifically crop production agriculture. Agriculture, being one of the most diverse, variable, uncertain, and biologically driven field production environments, focus on agriculture provided, in our opinion, the best example to discuss the fundamentals of robotics for field applications. The concepts, algorithms, and tools discussed in this book, though the examples come from efforts in crop production systems, are equally applicable to robotics beyond production agriculture, particularly for outdoor and field applications such as those common in animal farming, military, mining, and construction industries.

Summary and Concluding Thoughts

To summarize, automation and robotics is an increasingly important area of research, innovation, development, and commercial adoption in agricultural and field applications. The overall success in developing novel robotic solutions for complex agricultural and field problems requires advancement and innovative integration of various tools, techniques, and concepts including machine vision systems, other sensors and sensing systems, navigation and guidance techniques, modeling, simulation and control methods, manipulation and end-effector technologies, and robust machine learning techniques. This book has been developed to cover some of these important areas of robotics as it applies to field environments. The following are three most important features of the book:

(i) The first book discussing the fundamentals of this emerging technology in agriculture, which is suitable for senior-level undergraduate students and graduate students (as a textbook or reference book) and for researchers, engineers, policy makers, farmers, and other stakeholders as a reference book.
(ii) Use of a systematic approach to discuss the fundamentals of automation and robotics as it relates to agricultural and field applications supported by unique and emerging examples from cutting-edge research and development programs around the world.
(iii) The book has presented basic principles of generic concepts and technologies in agricultural robotics that is applicable to all areas of agricultural and field operations, including field crops, special crops, and green house and vertical farming, among others.

Last but not least, as we are drafting this preface, we are in the most unprecedented time of our generation, the COVID-19 pandemic. We are under complete lockdown (about two-thirds of the world population is in the same condition), and most of the latest editing and final polishing of this book occurred at small corners of our homes. This pandemic has reminded us how helpless we are, as individuals, under the vast, mighty force of nature. We hope, by the time this book comes out, we will be in a much better situation in relation to COVID-19. We also hope, however, that this pandemic is a timely reminder for us to play our roles on living a life that maintains a harmony with nature and a life that strives to optimize resource utilization for sustainable civilization. We would feel proud if this book, directly or indirectly, helps make the tiniest of impacts on advancing agricultural and field operations to be more efficient in conserving crucial natural resources.

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Manoj Karkee Dr. Manoj Karkee is an Associate Professor in the Biological Systems Engineering Department at Washington State University (WSU) and is the co-director of WSU-University of Technology Sydney joint center on #AgRobotics. He was born and raised in eastern hills of Nepal. He received his diploma in Civil Engineering and undergraduate in Computer Engineering from Tribhuvan University, Nepal. His MS was in remote sensing and GIS from Asian Institute of Technology, Thailand and his PhD was in Agricultural Engineering and Human Computer Interaction from Iowa State University. Dr. Karkee leads a strong research program in the area of sensing, machine vision and #AgRobotics at the WSU Center for Precision and Automated Agricultural Systems (CPAAS). He has published more than 65 peer-reviewed journal articles, and more than 25 referred conference papers. He has also been awarded two US patents, and has published one book (edited) and eight book chapters. Dr. Karkee is currently serving as an elected chair for International Federation of Automatic Control (IFAC) Technical Committee on *'Control in Agriculture'*, as an associate editor for *'Computers and Electronics in Agriculture' and 'Transactions of the ASABE'*, and as a guest editor for *'Sensors'* Dr. Karkee was recognized as *'2019 Pioneer in Artificial Intelligence and IoT'* by Connected World magazine and was featured as the *'Western Innovator'* by Capital Press. More about his research and scholarship can be found at https://labs.wsu.edu/karkee-ag-robotics/.

Qin Zhang Dr. Qin Zhang is the Director of the Center for Precision and Automated Agricultural Systems (CPAAS) of Washington State University (WSU), and a Professor of Agricultural Automation in the Department of Biological Systems Engineering, WSU. His research interests are in the areas of agricultural automation, agricultural robotics, and off-road equipment mechatronics. Prior to his current position, he was a faculty member at the University of Illinois at Urbana-Champaign, worked at Caterpillar Inc., and taught at Zhejiang Agricultural University in China. Based on his research outcomes, he has authored/edited seven books, written more than a dozen separate book chapters, edited three conference proceedings, published over 180 peer reviewed journal articles, and been awarded 11 U.S. patents. He is currently serving as the Editor-in-Chief for *Computers and Electronics in Agriculture*. Dr. Qin Zhang received his B.S. degree in engineering from Zhejiang Agricultural University, China; M.S. degree from the University of Idaho and Ph.D. degree from the University of Illinois at Urbana-Champaign. Dr. Qin Zhang is a member of Washington State Academy of Science and an ASABE Fellow and is serving or served as a guest or an adjunct professor for 9 other universities.

Chapter 1
Agricultural and Field Robotics: An Introduction

Qin Zhang and Manoj Karkee

1.1 Background

The primary purpose of agriculture is to produce sufficient high-quality food for human being to sustain and enhance life. Commonly accepted population growth models predict that there will be more than nine billion people by 2050 in the world, and the increasing population will significantly increase the demand for food, fiber, and fuel. People have historically improved and kept evolving farming technologies to meet the needs for feeding continuously growing human population by increasing productivity and production efficiency and enhancing food safety and nutrition while protecting the environment and conserving natural resources. One big challenge the agricultural industry of the United States (and so do many other countries) facing today is the shortage of human labors to conduct field operations, and the trend is expected to continue and become even worse.

One solution to address the field labor shortage challenge is the adoption of mechanized and automated farming technologies. Over the past century, mechanization technologies have made revolutionary changes in field crop production, making it possible to achieve high yields using minimal farm labor. Attributed to its great impact to societal advancement, agricultural mechanization was recognized as the seventh greatest engineering achievements of the twentieth century by the National Academy of Engineering of the United States. Continuing up on this success, mechanized farming has been advancing through adoption of increased level of automation and intelligence to further improve the precision management of crops (including input resources), increase productivity, and reduce farm labor dependency in field operations beyond what has been possible with conventional mechanization technologies. For example, farmers have widely adopted

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auto-steering technology commercialized early this century for many different field operations including tilling, planting, chemical application, and harvesting (Erickson 2019). Automated thinning and precise weeding in vegetable and other crops are other technologies that have recently been commercialized. Mechanization and automation/robotics have played similar roles in other field applications such as those common in construction, mining, and military industries. For agricultural and other field machinery to be capable of performing those automated field operations, machinery needs hold the abilities of (i) being aware of actual operation condition, (ii) determining corrections suitable for changed conditions, and (iii) implementing the corrections during field operation.

These three basic abilities required for automated or intelligent agricultural/field machinery actually are the same as those needed for robots which include the capabilities of (i) perceiving the situation of an operation with surrounding conditions, (ii) making appropriate decisions for smartly performing the operation under the condition, and (iii) automatically implementing the desired operation. Such similarity between desired abilities of intelligent agricultural and field machinery and robots makes a logical sense to call such machinery robotic machines. It implies that agricultural and field robots do not have to be in a form of human-like machines in appearance, but keep their conventional configuration for most effective, efficient, and robust field operations. Such a definition allows us to inherit the accomplishments of century-long development of agricultural and field machinery technology in creating robots for various agricultural and other field applications.

1.2 Fundamental Technologies for Agricultural and Field Robotics

1.2.1 Sensing and Situation Awareness

As mentioned earlier, the first capability of a robotic machine has to possess is its ability to perceive an awareness of the operational situation, which is acquired using sensors and/or sensing systems integrated with those machines. As a machine designed to mimic humans performing various tasks, ideally a robot should possess all the “senses” of human being, namely, vision, hearing, feel/touch, smell, and taste. However, robotic agricultural/field machines are designed to perform some specific tasks in some specific operational sites/conditions, and therefore, they often are not needed to have the full ability to sense to gain the needed awareness of the situation to conduct appropriate operations. In a wide range of agricultural and field applications, the ability to see is often sufficient, and therefore, visual sensing plays a critical role in many robotic machines designed and developed for agricultural and other fields.

The first fundamental sensing function requested by any mobile robotic machinery is the capability to gain an awareness of its surrounding and find its ways to move on the desired paths to perform the designated operations. Composed of image acquisition hardware and image processing software to automatically inspect the environment and objects of interest based on the visual characteristics, computer vision could provide the required capability (Reid et al. 2000). One of the widely used and simplest computer vision systems could probably be the monocular vision. Similar to one eye vision of human being, a monocular vision is capable of providing a two-dimensional (2D) visual perception on the relative positions of objects of interest within a field of view. This technique has found its application in detecting a guidance directrix on crop rows or the edges along harvested crops to guide robotic machinery performing different operations in row crop fields (Rovira Más et al. 2005). Various methodologies of image processing have been developed for extracting the guidance information for providing a steering signal for navigating the mobile robotic machinery (Reid et al. 2000). More discussion on various techniques used to acquire and process images can be found in Chap. 2. Although the 2D image approach is computationally efficient, it lacks reliable means to locate the actual position of an object of interest. From this point of view, binocular vision can be used to obtain a stereo view (3D image) of the scene and therefore to provide more robust perception on perspective pathways because of its capability of providing depth information. Furthermore, stereovision has two important advantages for navigating robotic machinery: (i) moderate insensitivity to shadows and changes in lighting conditions and (ii) its capability to provide useful state information to the tracking phase as the localization of potential obstacles in front of unmanned vehicles (Rovira Más et al. 2009).

Because agricultural and field robots are used on outdoor natural environment, it requires that surrounding awareness sensing on these machines need to have high robustness, high reliability, acceptable accuracy, high mechanical and temperature stability, and low cost. There are a few other sensing methods, such as global positioning systems (GPS), and laser scanning/LIDAR systems, which are widely used (stand-alone or in combination with other sensors using sensor fusion techniques) on robotic agricultural/field machinery to provide reliable positioning information for navigating such machinery operating in the field autonomously. Detailed description on stereovision and other 3D sensing techniques and systems can be found in Chap. 3.

Other than providing navigation information, vision sensors are also used in detecting other characteristics of object of interest either to support robotic operations or to scout crop growth/health conditions. To provide such functionalities, machine vision-based sensing techniques use different types of modalities to acquire appropriate information. Standard imaging sensors can be used to detect monochrome or color responses for determining physical properties of object of interest, such as relative location, shape, and/or size; and spectral imaging sensors can be used to detect responses in various bands of spectrum for measuring biological properties of plants, such as nutrient, water, and disease stresses of a plant. A few examples of standard image sensing applications (other than navigation) include weed detection for robotic weed control (Blasco et al. 2002), branch detection for robotic pruning of apple trees (Karkee et al. 2014), and apple detection for robotic picking (Silwal et al. 2016). Some examples of spectral image sensing include crop nitrogen stress detection (Kim et al. 2000; Noh et al. 2006), soybean disease detection (Cui et al. 2010), and blueberry fruit maturity detection (Yang et al. 2014). More discussion on spectral sensing techniques can be found in Chap. 4 and their applications on crop scouting can be found in Chap. 5.

One specific application of various sensing capabilities of a robot would be in automated phenotyping, which aims at performing high-throughput screening of genotypes for more effective breeding selection of crops and has gain high attention in recent years. As plant phenotyping attempts to measure plant growth, architecture, and composition of organs to canopies with a certain degree of accuracy and precision at different scales, both standard and spectral imaging methods have found their applications in measuring phenotyping parameters (Li et al. 2014). The commonly measured plant phenotype parameters include plant architectural data, such as plant height, stem diameter, color, leaf area, and leaf angle, and abiotic stress, such as drought and salinity adaptation, disease resistance, and yield (Berger et al. 2010; Arvidsson et al. 2011). One advantage of image-based sensing is its ability to acquire high-resolution data, which allows an ability to analyze and visualize plants/objects often using multidimensional, multiparameter, or sometimes multispectral information. Therefore, imaging sensors have been increasingly used to quantify plant phenotyping parameters both in controlled environments and in open fields (Walter et al. 2012; White et al. 2012; Sankaran et al. 2018). More discussion on various sensing systems and their applications in precision agriculture and plant phenotyping can be found in Chap. 6.

In addition to visual sensing (and spectral imaging, as an extension of visual sensing), some other sensing methods can also be used to mimic human's capability to gain a comprehensive situation awareness to support robotic agricultural/field machinery performing some specific tasks. A few examples include the use of electronic nose or electronic tongue to determine the maturity or quality of some produces based on their smell or taste (Gómez et al. 2006; Ulloa et al. 2013) and the use of acoustic sensor to measure the canopy density in orchards and vineyards in terms of reflectance of ultrasonic sound (Palleja and Landers 2015). Many operations in agricultural production require some interaction between the machinery and the crops or animals which are often very sensitive to magnitude of mechanical impacts, and some types of touching force/impact sensing could also be necessary for some situations.

It needs to be pointed out that other than situation awareness sensing, robotic machinery may require to have other types of sensors for measuring operational parameters to achieve accurate controls of automated implementation. For example, an effective robotic apple picking may require the robotic machine to be equipped with position, speed, and/or force sensors on its manipulators and end-effectors for controlling the picking actuator quickly and accurately in reaching the target fruit and effectively removing it from the tree.

1.2.2 *Intelligent Decision-Making*

After obtaining the required perception ability, an essential ability to distinguish robotic machinery from conventional ones is its ability in making intelligent operational decisions in response to the perceived operation situations. One of the major challenges in making robotic agricultural/field machinery work properly and autonomously in different kinds of field is mostly caused by the high level of randomness in both the biological and physical properties, wide variations in geometric features of task/target targets, as well as the high level of uncertainty in operation conditions. To overcome these challenges, it demands the robotic machinery possesses the ability in making intelligent decision in terms of detected operation situation. One approach is to combine human workers and robots synergistically and allow the robot to mimic human experts' making intelligent operational decision by using examples from human experts making the decision in similar scenarios. One example of this approach is a farmer-assisted fertilizing robot developed by Vakilian and Massah (2017) for precise nitrogen management in greenhouse crops. Such an approach requires the robot to detect the operation scenario using onboard sensors, such as using a visual sensor to acquire textural features indicating crop growth condition, and check the detected indicators against a set of reference scenarios. After a matching scenario is found, the robot will then apply an adequate rate of fertilization similar to how a human worker will do for this reference scenario. This approach requires the availability of a set of reference scenarios with human workers' reaction for the case in similar scenarios. Another approach is to separate the sensing system from the robot (Zion et al. 2014), which is frequently proposed especially for harvesting robots. By mapping the harvesting targets in the field using an adequate coordinating system prior to harvest, the robot could reach a bank of targets according to the recorded coordinates. It could speed up the operation substantially as the sensing method is no longer a limiting factor to draw the robotic harvesting efficiency down, which is one of the major remaining challenges for agricultural and field robots.

In many field operations in agricultural production (and other similar applications), it is often desirable that the robotic machinery possesses substantial level of intelligence to work properly and effectively under highly uncertain and changing operation conditions. One way to solve such a problem is via learning from sample data. As a computational method that involves progressively improving the performance on a specific task through data-based learning, machine learning (ML) algorithms have been adopted in supporting decision-making on robotic machinery to avoid or minimize using explicitly developed programs or models. A few examples include the naïve Bayes (NB), k-mean clustering, support vector machines (SVMs), and k-Nearest Neighbor (kNN)-based ML algorithms (Rehman et al. 2019). Deep learning (DL), a class of extended classical machine learning methods created by adding more "depth" (or the complexity), is one of the newest and most robust ML techniques that enhances the capability of automated feature extraction from raw data (Kamilaris and Prenafeta-Boldú 2018). Therefore, DL is suitable for solving complicated intelligent control problems in agricultural and field applications. The advancement of machine learning (including DL) technologies has been and will continue to offer more useful tools in making intelligent operational decisions for agricultural and field robots.

1.3 Challenges and Opportunities

The main function of agricultural and field robots is to perform designated tasks automatically or autonomously on designated production/operation sites. As mentioned previously, tremendous progress has been made in the past century in developing and adopting mechanization technologies for agricultural and other field operations. Many modern agricultural machines that have been widely used in various production operations today were matured from decades of continuing improvement for achieving the best possible performance on doing the specific tasks. Similar improvements have been made in other field operations over the last several decades. These matured machines and machinery systems provide a rich resource and a strong foundation for developing actuation technologies for many agricultural and field robots.

There are still challenges for creating capable and effective robotic actuation technologies for doing the work today's agricultural and field machinery are not able to perform or could not effectively perform due to their low levels of intelligence. For example, the production of high-value specialty crops, which the US Department of Agriculture (USDA) defines as fruits and vegetables, tree nuts, dried fruits, horticulture, and nursery crops, is still largely dependent on manual labor. This dependence is mainly attributed to the lack of mature mechanization/automation technologies for various field operations such as fresh fruit and vegetable harvesting, tree training and pruning, crop pollination and thinning, and weed control, among others (Davidson et al. 2016). As a specific application example of robotic fruit harvesting, the key bottlenecks for commercial development of such a machinery are sensitivity of the produce quality to mechanical impact during harvesting and the extensive variability that exists in the unstructured orchard environment. The actuation technology (including the manipulator and end-effector) optimization for specialty crop harvesting applications is still an active area of research (Sivaraman and Burks 2007; Van Henten et al. 2009; Lehnert et al. 2015; Chap. 7 of this book). Hoeing actuators for intra-row mechanical weeding (Gobor et al. 2013) and string tying actuators for hops' production (He et al. 2012) are two examples of other actuation technologies need to be developed especially for robotic applications in the agricultural and field environments as there are either no existing mechanical devices available for performing the work or the existing devices are inadequate for performing robotic operations.

Powered by the recent technological advancement in machine learning, sensing and data processing techniques, as well as parallel computing, agricultural and field robots have never been so close to be practically used in field for commercial productions/operations. It creates an urgency for starting a new study on management of robotic field operations, consisting of robotic equipment selection, efficient utilization in the field, and optimization for economic returns.

Agricultural and field robots are developed, to a large extent, for solving the challenges of the human field labor shortage and improve worker health and safety, and these robotic machines have to be uniquely designed, normally for specific field operations. It forms an important feature to distinguish agricultural and field applications of robots from industrial operation: while industry applications could adopt robotic operation to a few selective tasks in a factory, agricultural applications would make sense only if the entire operation were robotized to solve the challenge of field labor shortage. Another basic consideration in equipment selection is proper sizing of robots. Proper sizing of robots for every field operation to optimally match their capacities plays an essential role for achieving productive, efficient, and profitable operations. Coordination strategies and control of multiple robots also play a critical role for productive, efficient, and safe operations.

One critical obstacle, specifically for agricultural applications, for effective utilization of robotic equipment is the insufficient skills of farmers to effectively manage, operate, and supervise robots as they could in using conventional machinery. Effective robot managing and supervision may include work-plan creation for individual robot and the entire robot fleet, system initialization, the operation-specific data/information management and utilization, and the override control for abnormal conditions, and many of those tasks require human-robot interaction. Such tasks normally require special skills to perform and are often beyond ordinary farmer's capability to manage. One possible solution for such a skill challenge might be professional services, either through robot management and maintenance services or through robotic operation services. The former is to provide technical support to help end users (e.g., farmers) managing and operating their robotic equipment, and the latter is to provide custom robotic field operation services for the end users.

1.3.1 Economics: A Critical Dimension

Like in any other commercial operations, economic performance of robotic farming (and other field operations) is one of the most important measures in robotic field operation management. An ideal robotic farming system, for example, should be able to perform a most productive operation at the lowest total cost. As agricultural production is often measured by the yield, one way to measure economic performance is by the total cost per unit of yield. The total costs for a robotic production should include the initial costs, the operational and maintenance costs, and the error (e.g., crop damage) costs. The initial costs are one-time expenses for purchasing, delivery, and maybe initial integration and calibration when applicable of the robotic equipment. As the lifespan of a robot is usually over multiple years (production seasons), it could be divided into per season costs in assessing its economic performance. The operational costs are more complicated to determine and can be calculated in annual (or per season) basis. This category of costs should include service costs (such as maintenance and repair costs), material costs (such as fuels and other applicable materials), and labor costs (such as for monitoring and supervision). The use of robot in agricultural production does not mean to completely eliminate human labor in the operation, but to replace human labors from tedious field work by using less but skillful operators to manage and supervise the robotic operation. The error cost is relatively difficult to calculate as there is no sufficient information supporting the estimation of what error in robotic operation would cause what yield reduction, but impact heavily to the overall economic performance of robotic production as any error could result in a substantial yield loss and the entire economic performance is based on the yield.

1.4 Concluding Thoughts

Manual operations in agriculture and other field environments are challenging: they are not only labor intensive but are laborious and pose health and safety risks. In the twenty-first century of social and technological development, people deserve and have the potential to move away from performing back-breaking and risky work, such as climbing up and down tall ladders with heavy load of fruit (e.g., 15 Kg) in manual tree fruit harvesting, by using robotic machinery. As discussed before, tremendous progress has been made over the last century in agriculture in developing and adopting mechanization and automation technologies to minimizing farming inputs such as fertilizer, water, and labor while improving crop yield and quality. Similar progresses have also been made in other relevant (field) industries such as construction and mining. Using the foundation provided by these matured machinery systems and through the integration of advanced tools and technologies, reliable, robust, and affordable robotic technologies could be developed for these industries. With the recent advancement in AI techniques such as deep learning, ever-increasing capability and decreasing cost of computational technology (including parallel computing), powerful but affordable sensing systems such as hyperspectral imagers and novel robotic solutions such as soft robotics, we can now envision a world where all labor-intensive and laborious farming/field operations are performed by autonomous machines. In this way of farming, we believe, the role of human workers will be to operate, collaborate with, supervise, and/or troubleshoot these machines (based on the nature of the autonomous machine) remotely from off-site offices. The future of farming, what we also call *smart farming* or *Ag 4.0*, we believe, will also see widespread adoption of qualitative decision-making in farming by intelligent machines using AI, IoT, and big data analytics (and in collaboration with human experts). What the Prime Minister of Canada, Justine Trudeau, recently said about general technological developments holds true in agriculture (and related industries) as well: "we have never seen this rapid advancement in agricultural technologies in the past and we will never be this slow again."

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Part I
Sensing and Machine Vision

Chapter 2
Sensors I: Color Imaging and Basics of Image Processing

Won Suk Lee and Jose Blasco

2.1 Introduction

The human eye is geared by nature to sense the difference between colors. In nature, the perceived color is mainly determined by the different types of pigments present in plants, such as chlorophylls, carotenes, xanthophylls, and anthocyanins, that offer information on the type and status of plants and their fruits. This is very important, for example, for harvesting robots or those that act according to the state of the plants. Likewise, color allows differentiating structural elements of the scene and obtaining information from the environment that is essential, for example, in autonomous guidance systems. Color cameras are the most widely used devices in artificial vision because they produce images similar to those perceived by the human eye, and are therefore widely used to automate agricultural operations in a framework of precision agriculture (Cubero et al., 2016). The acquisition technology of these images is very advanced, and there are also numerous techniques to analyze and obtain information from this type of images. To obtain good results, it is very important to acquire high-quality images. Therefore, the selection of the cameras and the lighting conditions for the images are very important, especially in field conditions where the images are poorly structured and the lighting conditions are changing. Subsequently, it is necessary to follow a series of basic steps in the image analysis. First, a preprocessing is necessary to improve the image and eliminate noise pixels to achieve faster and more efficient subsequent processing, followed by a segmentation operation to obtain the regions of interest. Finally, a feature

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extraction is required to obtain the desired information. For any of these tasks, it is essential to develop efficient, robust, and accurate processing algorithms.

This chapter is an overview of the main topics related to the basics of color imaging and image processing operations applied to robotics in agriculture. Due the limited scope of this chapter, readers are encouraged to read reference books to get into details of image processing, such as Gonzalez and Woods (2018) and Russ and Neal (2017).

2.2 Basics of Color Imaging

The spectrum visible to humans goes from violet light to red light (Fig. 2.1). When light strikes an object, it absorbs part of the light and reflects the rest, which is perceived by the human eye through the retina. The retina contains two different types of light-sensing photoreceptor cells, rods and cones. The rods are activated in low light conditions, while the cones usually contain three types of pigments that are sensitive to wavelengths of light corresponding to the colors red, green, and blue. Therefore, all the colors that humans can recognize are a combination of these primary colors (Goldstein 2010). In order to determine, measure and compare colors, precise methods are needed to represent the colors with unique values.

2.2.1 *Color Representation*

The objective of a color model is to facilitate the expression of the colors in a standardized way. In general, a color model is the mathematical description of a coordinate system and a particular space (color space) in which each color is represented only by a single point (Ibraheem et al. 2012). Color models are used to describe the

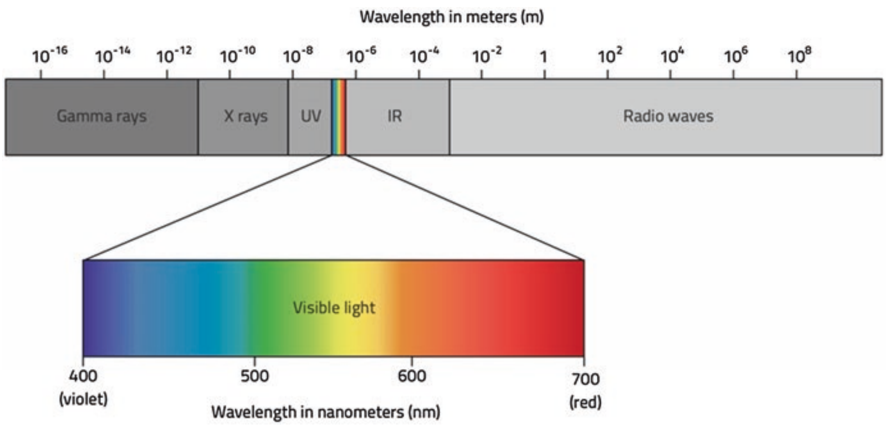

Fig. 2.1 Electromagnetic spectrum and the visible light

colors of digital images. In addition, a color space is a particular implementation of a color model that has a specific range of colors (Hastings and Rubin 2012). For example, in the RGB color model, there are different color spaces, such as Adobe RGB and sRGB. Different devices (for example digital cameras), due to the electronics and/or the software implemented on them, have their own color spaces and, therefore, can capture or represent only the colors within their range (Ford and Roberts 1998). There are a number of color spaces in common usage depending on the particular industry and/or application involved. For example, as humans we normally determine color by parameters such as brightness, hue, and colorfulness. On computers it is more common to describe color by three components, normally red, green, and blue. There are many different color spaces used in practice and each one represents a different method to describe the colors. Some of the most known models are briefly described below.

RGB Model

Red (R), green (G), and blue (B) or RGB model is the most widely used model in digital devices. It is based on an additive mixing model, where each color is formed by a combination of the three primary colors: red, green, and blue. The spatial representation is through a cube where each side measures 1 and each axis represents one of the three primary (RGB) color coordinates. In this model, the black color is represented at point (0,0,0) and the white color at (1,1,1). Figure 2.2b shows the distribution of the colors of the images in Fig. 2.2a, using the RGB color model.

A normalized variant of this model is defined as rgb, which is derived by dividing the RGB values by (R + G + B). As this color space is native for electronic devices, the RGB coordinates are commonly used in vegetation indices to assess different properties of the crops using remote sensing techniques (Meyer and Neto 2008).

HSV and HLS Models

These models were designed to be more easily understandable and interpretable since they use parameters more related with the perception of the color, such as hue, saturation, lightness (HSL), or value (HSV). Lightness (or value) of a color is the quality of being lighter or darker. Saturation means the difference of color with respect to a gray color with the same intensity. As saturation normally ranges between 0 and 1, the grey color would be 0 and the most colorful color would be 1. Hue can be defined as the dominant frequency of the spectrum. It is typically represented in a color wheel and expressed in angular degrees (°), with red being 0° (as well as 360°), green being 120°, and blue being 240°. Figure 2.2c shows the distribution of the colors of the images in Fig. 2.2a, using the HSV color model.

CIELAB and CIELUV Models

These models were defined by the CIE for industrial color applications where measurement and color comparison are important. The models separate a brightness channel (L^*) and two chrominance channels (a^*b^* and u^*v^*). The latter are defined by nonlinear transformations of the RGB model in order to achieve perceptually uniform representations of color. In these models, colors are presented such that the differences between perceived colors are related to the distance between these

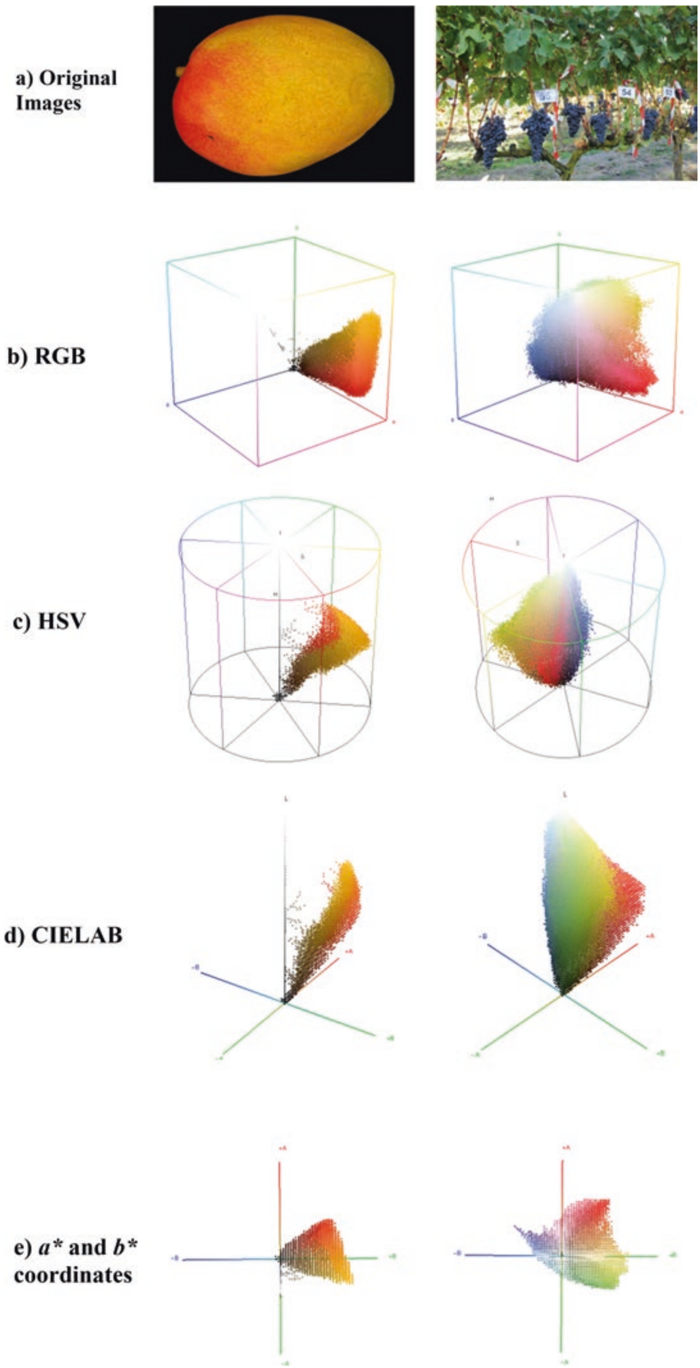

Fig. 2.2 Representation of the colors of two images, (**a**) one of a mango fruit and another of a vineyard using (**b**) RGB, (**c**) HSV, and (**d**) CIELAB color models. It can be seen how most colors are concentrated in a particular region of different color spaces, which indicates that in both fruit and vegetation images, only a relative small amount of colors is really used