BURLEIGH DODDS SERIES IN AGRICULTURAL SCIENCE

Robotics and automation for improving agriculture

Edited by Professor John Billingsley
University of Southern Queensland, Australia

burleigh dodds
SCIENCE PUBLISHING

Contents

Series list x
Acknowledgements xv
Introduction xvi

Part 1 Technologies

1 An overview of machine vision technologies for agricultural robots and automation 3
John Billingsley, University of Southern Queensland, Australia

1 Introduction 3
2 Basic concepts 4
3 The tools 5
4 The tasks 16
5 Future trends and conclusion 22
6 Where to look for further information 23
7 References 24

2 Advances in actuation and control in agricultural robots 27
Pål Johan From, Norwegian University of Life Sciences, Norway and University of Lincoln, UK; and Lars Grimstad, Norwegian University of Life Sciences, Norway

1 Introduction 27
2 Electric motors 28
3 Hydraulic actuators 30
4 Pneumatic actuators 30
5 Nozzles and metering orifice 31
6 Thermal methods 34
7 Optical-based management 34
8 Robotic manipulators 36
9 Control for precision agriculture 39
10 Case study: automated strawberry production 41
11 Summary 43
12 Future trends in research 44

13 Where to look for further information 45
14 References 45

3 Advances in communication systems in agricultural robotics 49
Christopher Wiegman, Santosh Pitla and Scott Shearer, The Ohio State University, USA

1 Introduction 49
2 The need for communication systems 51
3 Introduction to wireless communication 56
4 Person-to-machine communication 60
5 M2M communication 66
6 Security issues 71
7 Summary 72
8 References 73

4 Human–robot collaboration in agricultural robots 77
Yael Edan, Ben-Gurion University of the Negev, Israel

1 Introduction 77
2 Interaction roles 79
3 Levels of collaboration 80
4 Interface design 82
5 Tasks 86
6 Summary and insights for HRI in agriculture 88
7 Future trends in research 91
8 Where to look for further information 92
9 References 93
10 Further reading 96

5 Global positioning systems (GPS) for agriculture: an overview 101
John Billingsley, University of Southern Queensland, Australia

1 Introduction 101
2 How does the system work? 102
3 Improving accuracy 103
4 A peer-differential system 103
5 Future trends and conclusion 104
6 Where to look for further information 104

Part 2 Applications

6 The use of agricultural robots in crop spraying/fertilizer applications 109
Ron Berenstein, University of California-Berkeley, USA

1 Introduction 109
2 Challenges in current robotic sprayers 111

3 Case study: robotic sprayers in vineyards 113
4 Conclusion 128
5 Future trends 130
6 Where to look for further information 131
7 References 131

7 The use of intelligent/autonomous systems in crop irrigation 137
Stefano Carpin, University of California-Merced, USA;
Ken Goldberg, University of California-Berkeley, USA;
Stavros Vougioukas, University of California-Davis, USA;
Ron Berenstein, University of California-Berkeley, USA; and
Josh Viers, University of California-Merced, USA

1 Introduction 137
2 Related work 139
3 Overview of RAPID 142
4 Preliminary results 144
5 Future trends and conclusion 152
6 Acknowledgements 153
7 Where to look for further information 154
8 References 154

8 The use of agricultural robots in weed management and control 161
Brian Steward, Jingyao Gai, and Lie Tang, Iowa State University, USA

1 Introduction 161
2 Addressing the challenges of robotic weed control 164
3 Case study 175
4 Summary 177
5 Future trends in research 178
6 Where to look for further information 179
7 References 179

9 The use of agricultural robots in orchard management 187
Qin Zhang and Manoj Karkee, Washington State University, USA;
and Amy Tabb, USDA-ARS, USA

1 Introduction 187
2 Robotic pruning 189
3 Robotic thinning 191
4 Robotic spraying 194
5 Robotic harvesting 199
6 Robotic fruit transportation 202
7 Future trends and conclusion 204
8 Where to look for further information 207
9 References 208

10 Advances in automated in-field grading of harvested crops 215
Jose Blasco, María Gyomar González González, Patricia Chueca and Sergio Cubero, Instituto Valenciano de Investigaciones Agrarias (IVIA), Spain; and Nuria Aleixos, Universitat Politècnica de València, Spain

1 Introduction 215
2 Advantages of in-field sorting 218
3 Harvest-assist platforms 219
4 Case study: in-field pre-sorting of citrus 221
5 Summary 227
6 Future trends in research 227
7 Where to look for further information 228
8 References 229

11 Advances in using robots in forestry operations 233
Ola Lindroos and Omar Mendoza-Trejo, Swedish University of Agricultural Sciences (SLU), Sweden; Pedro La Hera, Swedish University of Agricultural Sciences (SLU) and The Cluster of Forest Technology, Sweden; and Daniel Ortiz Morales, Cranab, Sweden

1 Introduction 233
2 Challenges to using robots in forestry operations 237
3 Knowing the state of the machine 239
4 Knowing where the machine is located 240
5 Knowing the location of surrounding objects 240
6 Knowing how to plan the work 241
7 Moving around in the forest 242
8 Reaching and handling the trees 246
9 Converting trees into products 247
10 Extracting logs or trees to roadside landings 248
11 Remote-controlled operations 249
12 Conclusion 251
13 Future trends 252
14 Acknowledgements 253
15 Where to look for further information 253
16 References 255

12 Advances in robotic milking 261
Marcia Endres and Jim Salfer, University of Minnesota, USA

1 Introduction 261
2 Barn design considerations 263
3 Feeding management 265
4 Milk quality and udder health 268

5 Field observations 270
6 Summary and future trends 275
7 Where to look for further information 276
8 References 276

13 Advances in automating meat processing operations 279
Ai-Ping Hu, Georgia Tech Research Institute, USA

1 Introduction 279
2 Fish 280
3 Beef and pork 283
4 Poultry portioning and harvesting 286
5 Case study: intelligent deboning of poultry 288
6 Conclusion and future trends 295
7 Where to look for further information 296
8 References 297

Index 299

Introduction

Robotics and automation are having a significant impact on agriculture, one that is accelerating. This book reviews both key advances in their application and the research that is ongoing. It summarises developments in machine vision, navigation, actuation, communication and control technologies. In the second part of the book, ways are discussed to deploy these techniques to save labour, improve precision, speed and efficiency in agricultural operations. The state of the art is reviewed on the use of agricultural robots in applications such as crop spraying, irrigation and weed management. The book also addresses orchard management and harvesting, harvesting of soft fruit and in-field grading of harvested produce. It also reports on the application of robotics in the livestock sector.

Part 1 Technologies

The first part of the book discusses those robotic technologies that are of use in agriculture. Chapter 1 opens the volume by examining machine vision technologies for agricultural robots. After outlining basic concepts of machine vision and processing techniques, the chapter looks at the tasks to which they can be applied, from machine guidance and navigation to pest and disease identification as well as sorting fresh produce.

Moving on from machine vision, Chapter 2 looks at advances in actuation and control in agricultural robots. In recent years, agricultural robots have moved away from being pure sensor-carrying platforms for gathering data in the field into becoming action-delivering platforms providing physical interaction with the environment. The chapter discusses the actuation methods that are most commonly used on intelligent agricultural robots in order to control motion, physical interaction or manipulation. These actuation methods consist of both traditional actuators that have been transformed into precision farming tools, and novel actuators enabled by robotics and autonomous systems. The chapter introduces each actuator type before giving examples in agriculture. It concludes with a case study that looks at the way different actuators are used to automate strawberry production.

The subject of Chapter 3 is advances in communication and control systems in agricultural robots. Unmanned agricultural ground vehicles (UAGVs) have substantial potential to optimize crop yields and increase sustainability. Advances in sensing, communication, and control technologies coupled with Global Navigation Satellite Systems (GNSS) and Geographical Information Systems (GIS) are driving the transition from simple, off-road mechanical machines to machines with intelligence. Controller area networks (CAN) and

GNSS are contributing to the accelerated transition of tractors to become highly automated. These systems need to be safe and robust while operating in sub-optimal conditions compared to other autonomous systems. The variables encountered in the field, such as ground conditions, weather and the sheer size of the operations, highlight just a few of the challenges they face. The chapter shows how developments in communications technologies can help address these challenges. It introduces wireless communication before moving on to consider communication layers, network topology and communications technologies. The chapter considers person-to-machine (P2M) (cellular networks and MIMO broadband radio antenna networks) and machine-to-machine (M2M) (Wi-Fi, Bluetooth, ZigBee, 6LoWPAN and RFID) communication. Finally, the chapter discusses security issues.

Broadening the scope from purely robotic systems, Chapter 4 looks at advances in human-robot collaboration in agricultural robots. These are being developed for many on-farm tasks; though in practice current working agricultural robotics systems are still limited and fully robotized farms are not yet available. The chapter discusses the various types of interaction humans may have with robots and levels of human-robot collaboration. The chapter covers aspects of interface design and human-robot collaborative tasks such as detection, navigation, harvesting and spraying. The chapter concludes that the role of humans in agriculture will not be eliminated by introducing robotic systems and, should more autonomous systems become feasible, humans will still be needed for supervision and collaboration.

The section concludes with a brief overview in Chapter 5 of global positioning systems (GPS) for agriculture. In explaining how the system works, the technical concepts of code and carrier pseudo-ranges are mentioned, to focus on ways in which accuracy can be improved. Base stations and peer-differential systems are making an impact, while new constellations of satellites are promising to improve errors to a few centimetres even for low-cost systems.

Part 2 Applications

The second part of the volume looks at applications of robotic technology in agriculture. Chapter 6 examines the use of agricultural robots in crop spraying. A robotic sprayer can help reduce pesticide application while removing the human operator from the hazardous pesticide environment. The chapter provides an introduction to robotic sprayers and key challenges such as guidance and mapping, target detection and control. It includes a detailed case study of the development of a smart robotic sprayer for use in spraying vineyards, including the development of key components such as an automatic adjustable spraying device. The chapter also describes the development of an operational framework supporting human-robot collaboration.

The subject of Chapter 7 is the use of intelligent/autonomous systems in crop irrigation. Climate change, combined with the need to feed an increasing population with decreasing arable land, requires a radical re-think of the way water is delivered to crops to increase efficiency and minimize wasted water. The chapter examines how robotic and artificial intelligence can be used to improve precision irrigation in vineyards. The chapter pays particular attention to RAPID (Robot Assisted Precision Irrigation Delivery), a novel system currently being developed and tested at the University of California. The chapter presents some of the preliminary results from RAPID testing.

Chapter 8 considers the use of agricultural robots in weed monitoring and control. Weed control is essential for the production of high yielding and high-quality crops, and advances in weed control technology have had a huge impact on agricultural productivity. Any effective weed control technology needs to be both robust and adaptable. Robust weed control technology will successfully control weeds in spite of variability in the field conditions. Adaptable weed control technology has the capacity to change its strategy in the context of evolving weed populations, genetics and climatic conditions. The chapter focuses on key work in the development of robotic weeders, including weed perception systems and weed control mechanisms. The chapter addresses the challenges of robotic weed control, focussing on both perception systems, which can detect and classify weed plants from crop plants, and weed control mechanisms, covering both chemical and mechanical weed control. The chapter provides a case study of an automated weeding system.

Shifting from the field to the orchard, Chapter 9 looks at the use of agricultural robots in orchard management. The use of robotic or automated machines in orchard operations is primarily a response to growing labor shortages and costs. The introduction of robotic technologies is critical for improving yield of high-quality fruit with minimal dependence on seasonal human labor. The chapter provides an overview of robotic technologies for major tree fruit production tasks, including robotic pruning, thinning, spraying, harvesting and fruit transportation.

Chapter 10 turns to advances in automated in-field grading of harvested crops. Mechanical harvesting machines such as canopy and trunk shakers are widely used for the collection of some crops; however, most fruits and vegetables produced for the fresh market have to be collected manually. The chapter reviews the current state of mechanized collection technology, such as the development of harvest-assist platforms, as well as the possibilities of these machines to incorporate artificial vision systems to perform a pre-grading of the product in the field. The main advantages of each system are discussed and the problems encountered in the field are described. The chapter presents a case study on the use of harvest-assist platforms in citrus orchards, describing prototypes that are capable of both inspecting collected fruits and separating them into categories using computer vision.

Turning from fields and orchards to forests, Chapter 11 deals with advances in using robots in forestry operations. Advances in automation will enable forestry operations to be conducted in a more sustainable way. The chapter examines the challenges associated with using robots in forestry operations, focusing on the importance of knowing the state of the machine, where the machine is located, the location of surrounding objects, and how to plan work tasks. The chapter looks at the challenges of moving around in the forest, reaching and handling the trees, converting trees into products, and extracting logs or trees to roadside landings. The chapter also considers remote-controlled operations.

Chapter 12 moves to dairy production, considering advances in robotic milking. In recent years, growth in the number of robotic milking installations on farms has been driven by the need for better labour management and also for improved quality of life for dairy producers. The chapter reviews published research on such robotic milking systems (RMS), considering barn design, feeding management, and udder health in automated systems. The authors' field observations on RMS herds in Minnesota and Wisconsin, USA, are also included. The chapter covers feeding cows in RMS, milk quality and milk production using RMS and the economic considerations of implementing RMS on the farm. The chapter concludes that the trend towards robotic milking is set to continue into the future and the percent of dairy farms around the world using automation for milking their cows will further increase.

The volume's final chapter, Chapter 13, looks at advances in the use of robots in meat processing operations. Meat processing presents a particular challenge to robotics, as it deals with deformable biological products that lack uniformity, which makes automation extremely challenging. The chapter surveys advances in robotic automation of the processing of fish, beef, pork and lamb, as well as poultry, providing a detailed case study of the latter based on the author's own research.

Chapter 1

An overview of machine vision technologies for agricultural robots and automation

John Billingsley, University of Southern Queensland, Australia

1 Introduction
2 Basic concepts
3 The tools
4 The tasks
5 Future trends and conclusion
6 Where to look for further information
7 References

1 Introduction

A mere two-and-a-half decades ago, when our own research concerned machine vision for tractor guidance, the equipment involved a tower-case computer, a black-and-white CRT monitor and a 'Video Blaster' card to grab video stream from a camcorder mounted on the roof of the tractor. Today everything that is needed can be found within a supermarket smartphone that might cost well under a hundred dollars. As an OEM component the price of the camera used in such a phone is measured in cents. When attached to drones, cameras such as this can enable video to be captured, storing hours of image data on a microSD card that is smaller than a little fingernail.

Vision is becoming an essential solution to a vast array of control and measurement tasks, not least on the farm. Any attempt to nail applications down to the equipment and the software of the day runs the danger of becoming obsolete within a very few years. The names of research topics come in and out of fashion. The fundamental principles endure, but are christened with new titles that herald a parade of papers.

Control theory has seen fashions of 'modern', adaptive, predictive, variable structure, neural and fuzzy, to name but a few. The essence of the latter pair is the synthesis of nonlinear functions of multiple variables with back-propagation

http://dx.doi.org/10.19103/AS.2019.0056.03

being used for adaptation. Convolution and correlation underlie the techniques of systems analysis and now 'deep learning' is taking to the stage.

'Deep learning' has already entered the vocabulary of vision research and no doubt there are many more terms to come. But one thing is certain. The greatest impact will continue to be made by advances that are powered by their application in the mass market.

Today every smartphone can not only locate a face in the image, but even assess the quality of the smile of the subject. Surveillance cameras are adept at identifying faces. Here is a technology that can be borrowed and adapted for agricultural use, whether to grade vegetable by shape or identify cattle as individuals.

Some of the more elementary principles of machine vision will be detailed here, but in general this chapter will attempt a broad analysis of the tasks that can be helped by vision and the possibilities for its application.

2 Basic concepts

In general, the main functions of vision are location and recognition. Location allows a vehicle to be guided and fields to be mapped. Recognition allows the thing that you are locating to be identified, such as a tree to be avoided, a ripe fruit to be harvested or a weed to be killed.

In many ways, computer vision has the potential to be greatly superior to the human eye for both functions, though the eye colludes with the brain to achieve some remarkable results of its own. In the human eye, a colour is perceived as the ratios of just three measurements, seen primarily as red, green and blue. Video systems exploit this by measuring and showing just three sets of red, green and blue dots on the screen. But visible light consists of a continuous spectrum of wavelengths which can carry very much more colour information than the human eye can differentiate.

When red light is added to green light, the result is seen as yellow. The light from a sodium street light is also seen as yellow. But in the mixture of red and green light, an object with red and green stripes will show them clearly as colours, while in sodium light they will merely appear as shades of grey.

Common camera sensors peer through a multicoloured film of dots to give an image in three planes of red, green and blue. Though the sensor can detect light a substantial way into the infrared and ultraviolet, these are blocked by a filter in the lens. Monochrome intruder cameras are the exception to this. By adding a specialised colour filter, such a camera can be made sensitive to any combination of wavelengths we choose. By comparing views through two different filters, colour differences can be perceived that the human eye cannot discern. The name given to this is 'multispectral vision' or 'microspectral vision'.

2.1 Discrimination by colour

Discrimination by colour can be implemented in many ways. Of course, in many cases the differences can be seen in the conventional views. If this is not the case, two or more cameras could be used, but it can be more expedient to spin filters of special colours in front of a single camera, as was done in the very early television systems. Simpler still is to split the view of a single camera between stripes of filters and use the progress of the vehicle to move the image of the plant from one colour filter to the next. With autonomous machines that can work at night while the farmer is asleep, lights of special wavelengths can be used instead of filters.

Because illumination is not uniform, it is necessary to consider ratios, rather than absolute brightness. To give an example, a blue object will look brighter than a red one in blue light, but darker than that red one in red light, however bright the lights are. So when seeking to see a colour difference in two sorts of leaf, a spectrophotometer can be used in research to find at least two wavelengths where in one A is more reflective than B, while in the other the reverse is true. Once those wavelengths have been determined, coloured plastic filters can be sufficient to perform the comparison.

2.2 Recognition by shape

The human brain tends to see images in terms of outlines rather than patches of shades. One of the tricks of the eye is to ‘invent’ lines between areas of slightly differing brightness, as can be seen in Fig. 9. This strongly suggests that outlines are a better basis for object recognition than correlation of the pixels of an image. In graphic computer art there are several ways to represent an image. The original form is the ‘bitmap’, an array of coloured pixels, as in a .gif, .jpg or .png file. But gaining more prominence is the SVG, scalable vector graphic, that represents a set of outlines of areas each filled with a colour.

By tracing the outline of an object, its shape can be encoded in many fewer bytes. Even fewer bytes are needed to define an ‘s-psi’ plot. This represents the angle of a tangent as we move around the entire circumference. By encoding the angle as an 8-bit byte, giving increments of just under one-and-a-half degrees, a meaningful outline can be defined in just 256 bytes. This s-psi plot will be the same for all objects of the same shape, whatever their size. If the object is tilted, the plot values have a constant added to them. So the s-psi plot represents the shape in a form that is much simpler to use for identification by matching against templates.

3 The tools

Many of the figures in this chapter have been captured from JavaScript applications that can be found at www.essdyn.com/vision. Some of these show a window of code that can be changed in a browser to experiment with new values.

3.1 The camera

Evolving from the 'flying spot scanner' of the early days of television, today's cameras still use the concept of a 'raster'. The view is scanned by a line that runs left to right, moving down the picture from top to bottom to present a frame of data. In digital terms, each spot of the image is a 'pixel', so in a full HD scan of 1080 lines of 1920 pixels they number a couple of million, arriving at some fifty million per second. From this barrage of data our purpose might be to resolve a simple binary question such as 'is it a weed?' or just to obtain a couple of numbers defining the location of a landmark.

The software driver of the camera will grab each frame to the computer memory as a string of bytes, 3 or 4 to a pixel. Though one might think of these bytes as an array laid out as an image, they are in fact just a linear sequence. The pixel at location (50, 100) is held by the bytes starting from location (100 * width + 50) times the number of bytes per pixel. So until the fundamental camera design changes, any software has to start with this data set in order to extract the information that will perform the actual control or identification.

3.2 Image processing

Many software libraries exist with routines for processing image or video information, of which one of the best known is 'Open CV' (2018). Many of the functions in these libraries have the purpose of making the image more appealing to look at, such as 'filters' that identify edges, or sharpen or blur images by adding weighted sums of neighbouring pixel values.

The filter consists of a matrix of weights and can be thought of as a 'patch'. The patch is moved to be centred over each pixel of the image in turn then the sum is taken of each weight times the pixel value beneath it. The result is a new array of pixel values to be displayed.

3.3 Binary images

For shape analysis, images are often subjected to a threshold to simplify their analysis. Consider a very simple binary image, where each pixel is represented as either black or white, denoted by a value of either 0 or 1. It might appear as Fig. 1.

It can be 'smoothed' by adding up the pixel values in a 3 by 3 patch. The totals are shown in Fig. 2.

The new value of the central pixel is then set to 1 if the total exceeds 4, or to 0 otherwise, as shown in Fig. 3.

This has removed the straggling pixels and holes. It can be regarded as the application of the filter patch

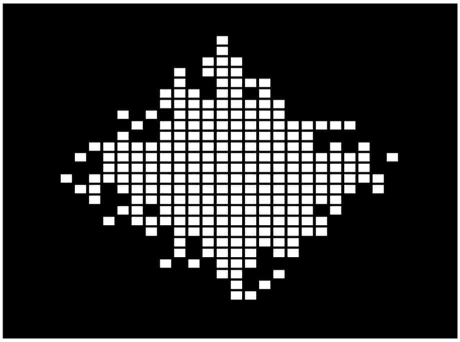

Figure 1 Rough binary image.

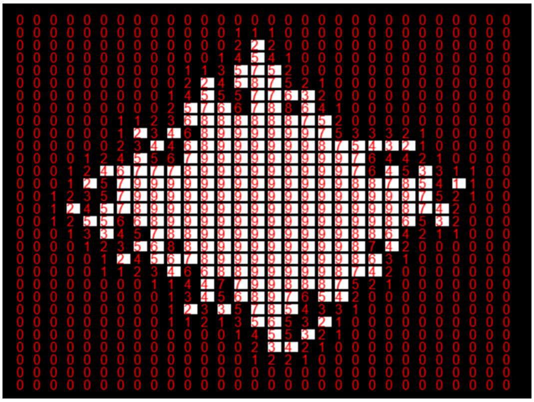

Figure 2 Numbers are shown for calculating smoothing.

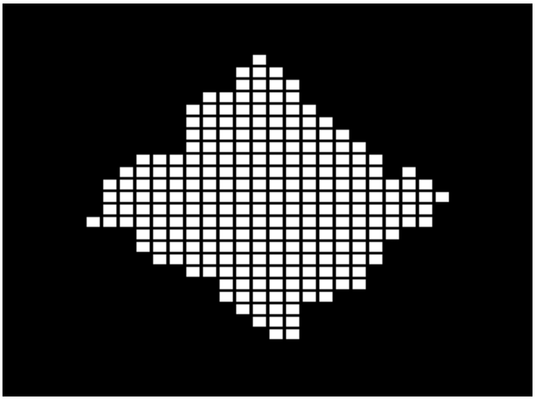

Figure 3 Result of smoothing.

Index

2D image plane 168
3D laser ranging system 196
3D line scan camera 282
3D machine vision system 289
3D point cloud 168, 169, 176
3D-printed beak-shaped gripper 287
3D scanner 13
3D shape features 168, 169
3D structural features 168
6LoWPAN. *see* Low Power Wireless Personal Area Networks (6LoWPAN)
Access point (AP) 58, 64, 66, 67–68
AC motors. *see* Alternating current (AC) motors
Actuators and control 43–45
  automated strawberry production 41–42
  electric motors 28–30
  hydraulic actuators 30
  nozzles and metering orifice 31–33
  optical-based management 34–36
  overview 27–28
  pneumatic actuators 30–31
  precision agriculture 39–41
  robotic manipulators 36–39
  thermal methods 34
Adam algorithm 146
Adaptable manipulation 283
Adaptable weed control technology 161
Adaptive controllers 40
Adjustable spraying device (ASD) 114–116, 127, 128–129
  design and characteristics evaluation 116–119
  performance evaluation 120, 122–124
Advanced Encryption Standard (AES) 72
Advanced machine vision 34, 42
Aerial platforms 198
AES. *see* Advanced Encryption Standard (AES)
Agricultural Engineering Centre 221
Agri-robotic platforms 124–128
  description 124–125
  integrative site-specific sprayer experiment 125–128
AI. *see* Artificial intelligence (AI)
Alternating current (AC) motors 29
Antioxidant enrichment 36
ANYmal 243
AP. *see* Access point (AP)
Application programming interface (API) 56
Aponeurosis 285
Application layer 57
Arduino 15
Artificial intelligence (AI) 162
Artificial pollination 198
ASD. *see* Adjustable spraying device (ASD)
Australian Center for Field Robotics 171
Australian Maritime Safety Authority 103
AutoCart System 52
Automated robot control system 203
'Automation and Remote Controlling of Forest Machinery' 234
Auxiliary hydraulic valves 30

Bayesian classifier 200
Bayesian Neural Networks 144
'BBC Micro:bit' 15
BB control approaches. *see* Behavior-based (BB) control approaches
'Beast system' 250
Behavior-based (BB) control approaches 49, 51
BeiDou system 101
Binary images 6, 8
Binocular vision 15
Biological morphology characteristics 167–169
Bitmap 5

BLDC motors. *see* Brushless DC (BLDC) motors
BlueRiver device 130
Bluetooth 57, 59, 67, 68–69, 72
Bluetooth Special Interest Group 68
Boston Dynamics 243
Broad-spectrum monochrome camera 19
Brushless DC (BLDC) motors 29

Cable yarders 248
Cameras 6, 15
Camera sensors 4
CAN. *see* Controller area network (CAN)
CANbus 41
Canopy image classification 201
Canopy shakers 218
CCD. *see* Charge-coupled device (CCD)
CCOBP3P. *see* Constant Cost Orienteering on BP3 Problem (CCOBP3P)
Cellular networks 61–63
Charge-coupled device (CCD) 113, 129, 166, 281
CIS. *see* Cranab Intelligent System (CIS)
Climate Corporation 62
Clinical mastitis (CM) 269
Clinton, Bill 103
Cloud computing 56
CM. *see* Clinical mastitis (CM)
CMOS. *see* Complementary metal-oxide-semiconductor (CMOS)
CNN. *see* Convolutional neural networks (CNN)
CNNCF. *see* Convolutional Neural Networks Correlated Field (CNNCF)
CNNUP. *see* Convolutional Neural Networks Uncorrelated Plants (CNNUP)
Cognitive factors 90
Colours and grey scales 9–10
Colour sensing 19
Communication 41, 59–60
Communication systems 73
  M2M communication 66–71
  need for 51–56
  overview 49–51
  person-to-machine 60–64, 66
  security issues 71–72
  wireless 56–60
Complementary metal-oxide-semiconductor (CMOS) 166
Computer-Supported Cooperative Work 80
Computer vision 4, 16, 38, 224, 240, 281
Constant Cost Orienteering on BP3 Problem (CCOBP3P) 150
Control input devices 83
Controller area network (CAN) 49, 69, 239
Control schemes 39–40
Control theory 3
Convolutional neural networks (CNN) 143, 146, 153, 178, 192, 196, 201
Convolutional Neural Networks Correlated Field (CNNCF) 146, 147
Convolutional Neural Networks Uncorrelated Plants (CNNUP) 146
CPS. *see* Cyber-physical systems (CPS)
Cranab Intelligent System (CIS) 246
Crop plant classification 176
Crop sensing systems 32
CTL. *see* Cut-to-length (CTL) harvesting system
Customized perception 283
Cut-to-length (CTL) harvesting system 235, 238, 239, 240, 242, 244
Cyber-physical systems (CPS) 52, 53, 54–55
Cycloid hoe concept 173

Data
  driven approach 144
  handling 54
  link layer 57, 58
  preprocessing 176
DC motors. *see* Direct current (DC) motors
Decision support systems (DSS) 235, 241–242, 247
Deep learning (DL) techniques 3, 130, 178, 200
Deere and Company 52
Deficit irrigation. *see* Stress irrigation
Degree-of-freedom (DOF) 124, 282, 284, 285, 288, 289, 290, 292, 293, 294
Delta robot 37
Depth-to-water (DTW) maps 242
Differential GPS 103
DigiMesh 70
Digital agriculture 54, 56
Digital I/O devices 221
Dino robot 172
Direct current (DC) motors 29
Directional guidance 86
DL. *see* Deep learning (DL) techniques
DOF. *see* Degree-of-freedom (DOF)
DSS. *see* Decision support systems (DSS)
DTW. *see* Depth-to-water (DTW) maps

Dynamic hybrid position/force control method 292

EC. *see* Electrical conductivity (EC)
EcoRobotix spraying robot 171
Elastomer (EPDM) metering 31
Electrical conductivity (EC) 268–269
Electric motors 202
EPCglobal 71
EPDM. *see* Elastomer (EPDM) metering
Error prevention and recovery 89
Excess green index (ExG) 166
ExG. *see* Excess green index (ExG)

FarmMobile Puck 62
FAST. *see* Features from accelerated segment test (FAST)
Faster R-CNN 196, 201
FCC. *see* Federal Communications Commission (FCC)
FCC Broadband Deployment Report (2018) 62
Feature-based localization refinement 176
Feature extraction 176
Features from accelerated segment test (FAST) 167
Federal Communications Commission (FCC) 61, 62
Field View 62
Finite differences 139
Fin Ray principle 202
'FIR' finite impulse-response filter 10
Fixed automation 280, 283
Fixed orifice nozzles 31
FKP. *see* Network area corrections (FKP)
Flaming process 34
FLIR D46-17 117
Food Processing Technology Division (FPTD) 288, 289, 290, 291–292, 295
Forest Harvesting Mechanization and Automation 234
Forestry operations 251–253
  challenges 237–239
  converting trees
    decision support 247
    product properties 247–248
  extraction 248
  features 239–240
  locating machine 240
  movement 242
    following planned path 244–246
    locomotion in rough terrain 243–244
  overview 233–235
  planning 241–242
  reaching and handling trees 246–247
  remote-controlled operations 249–250
  sensing surroundings 240–241
FPTD. *see* Food Processing Technology Division (FPTD)
Frank Poulsen Engineering Aps. 173
Freeman Chain 12
Free traffic flow 263
Fungal and disease management 35–36

Gabor wavelet transformation 167
Galileo 101
Garford Farm Machinery Ltd 173
Genetic algorithm 201
Geographical Information Systems (GIS) 49, 56
Georgia Tech Research Institute 288
GIS. *see* Geographical Information Systems (GIS)
Global Navigation Satellite System (GNSS) 49, 101, 111, 226, 240
Global positioning systems (GPS) 16, 18, 20, 61, 111, 130, 171, 203
  improving accuracy 103
  overview 101–102
  peer-differential system 103–104
  working 102
GLObal NAvigation Satellite System (GLONASS) 101
GNSS. *see* Global Navigation Satellite System (GNSS)
GPR. *see* Greedy partial-row (GPR)
GPR heuristic 151, 152
GPS. *see* Global positioning systems (GPS)
Graphics processing unit (GPU) 38–39
Greedy partial-row (GPR) 150, 151, 152
Greedy row 150
Griefenberg TG 1100 248
Ground platforms 198
Ground vehicle–based sensing 164–165, 167
Guided traffic flow 263

HART. *see* Highway Addressable Remote Transducer Protocol (HART)
High Speed Packet Access (HSPA) 61
Highway Addressable Remote Transducer Protocol (HART) 60
Histogram of gradient (HOG) 167
HiVision system 250

HO. *see* Human operator (HO)
HOG. *see* Histogram of gradient (HOG)
HRC. *see* Human-robot collaboration (HRC)
HRI. *see* Human–robot interaction (HRI)
HSI. *see* Hyperspectral imaging (HSI)
HSPA. *see* High Speed Packet Access (HSPA)
HSV. *see* Hue-saturation-value (HSV)
HTTP. *see* HyperText Transfer Protocol (HTTP)
Hue-saturation-value (HSV) 166
Human-machine interfaces 56
Human operator (HO) 80–81, 86, 88, 89
Human–robot collaboration (HRC) 91–92
  interaction 88–89
    roles 79–80
    usability evaluation 90
    see also Human–robot interaction (HRI)
  interface design 82–85
  levels 80–81
  overview 77–79
  tasks 88
    detection 86
    harvesting 86–87
    navigation 86
    spraying 87
Human–robot interaction (HRI) 78, 80, 83, 142
Hyperspectral imaging (HSI) 166
HyperText Transfer Protocol (HTTP) 57, 58, 66

IBC. *see* Intelligent boom control (IBC) system
Identify Friend or Foe (IFF) 70
IEEE 802.15.4 57, 59, 70
IEEE 802.11 standard 59, 67
IFF. *see* Identify Friend or Foe (IFF)
IG. *see* Irrigation graph (IG)
Image acquisition software 118
Image analysis 38
Image blurring and sharpening 10–11
Image processing 6, 122, 127, 140
Image segmentation 225
Image stitching 141
Image tracing 12–13
In-field sorting 227–228
  advantages 218–219
  of citrus 221–226
  harvest-assist platforms 219–221
  overview 215–218
'Infinite impulse response' filter 10
Information presentation 89
Intel Core i7-6850k 147
Intelligent boom control (IBC) system 246
Intelligent control algorithms 41
Intelligent controllers 40
Intelligent Deboning System 295
Intelligent management system 203
Intelligent valve 246
Intel RealSense 196
Interaction effectiveness and efficiency 89
International Union of Forest Research Organizations (IUFRO) 234
Internet of things (IoT) 59, 67, 139
Internet Protocol (IP) 57, 70
Inter-UAGV communications 54
Intra-row weeding 173–174
IoT. *see* Internet of things (IoT)
IP. *see* Internet Protocol (IP)
IPv6 57, 58
Irrigation graph (IG) 149
Irrigation sensor 140
ISOBUS 41
IUFRO. *see* International Union of Forest Research Organizations (IUFRO)
IVIA. *see* Valencian Institute of Agricultural Research (IVIA)

Jaybridge Robotics 52
John Deere 909 feller-buncher 249
John Deere Ltd. *see* PlusTech Ltd

Kinect 3D scanner 15
Kinect v2 sensor 169
Kinze Manufacturing, Inc. 52
Kongskilde Robotti 172
Konrad KMS 12Uxii 248

Ladybird robot 171
LAN. *see* Local Area Networks (LAN)
Laser 34
Laser distance sensor 117
LBP. *see* Local binary pattern (LBP)
Levels of collaboration/automation (LOA) 78, 81, 84
LiDAR. *see* Light detection and ranging (LiDAR)
Light-based 3D cameras 216
Light detection and ranging (LiDAR) 13, 15, 168, 242
Light-emitting diodes (LEDs) 221, 223–224
Limb-to-trunk ratio (LTR) 190
Linear actuators 29
Linear feedback controllers 40
Linear hydraulic actuators 30

Linear-quadratic-Gaussian controller 40
Linear-quadratic regulator 40
LOA. *see* Levels of collaboration/automation (LOA)
Local Area Networks (LAN) 61
Local binary pattern (LBP) 167
Long-term evolution (LTE) 61–62
Low-altitude aerial-based sensing 165, 167
Low-pass filter 10–11
Low Power Wireless Personal Area Networks (6LoWPAN) 57, 58, 70, 72
LTE. *see* Long-term evolution (LTE)
LTR. *see* Limb-to-trunk ratio (LTR)
Lyapunov function 40
Lyapunov theory 40

M2M. *see* Machine-to-machine (M2M) communication
Machine automation 54
Machine learning 38, 144
Machine-to-machine (M2M) communication 54, 66–71
  see also specific entries
Machine vision 164
  sensors 171
  system 195
Machine vision technologies 23
  applications to livestock 22
  concepts
    discrimination by colour 5
    recognition by shape 5
  guidance and navigation 16, 18
  overview 3–4
  packing 22
  pests and weeds identification 19–20
  post-harvest grading and sorting 21
  ripe fruit identification 20
  tools 5–15
MATLAB software 120, 127
Meat processing operations 296
  beef and pork 283–286
  fish 280–283
  intelligent deboning
    characterizing non-uniform product 289–290
    correcting for deviations 291–295
    nominal cutting paths 290–291
  overview 279–280
  poultry portioning and harvesting 286–288
Mechanical weeders 171–175
Mesh topology 59, 68, 70
Microcontrollers 40–41
Microsoft Kinect 190, 196, 201
Microsoft LifeCam Studio 117
Microsoft Visual Studio 117
Microspectral vision 4
Microwave radiation 34
MIMO. *see* Multiple-Input and Multiple-Output (MIMO) broadband radio antennas
Mobile manipulator systems 37–38
Model-predictive controllers (MPCs) 40
Monochrome intruder cameras 4
MPCs. *see* Model-predictive controllers (MPCs)
MRTA. *see* Multi-robot task allocation (MRTA)
Multilayer perceptrons 144
Multiple-Input and Multiple-Output (MIMO) broadband radio antennas 59, 61, 63–64, 66
Multi-robot task allocation (MRTA) 141
Multispectral analysis 19, 21
Multispectral approach 20
Multispectral vision 4, 19
MyJohnDeere.com 62

Naio Technologies 172
National Robotics Initiative 138
National Science Foundation 138
NDVI. *see* Normalized difference vegetation index (NDVI)
Network area corrections (FKP) 60–61
Network layer 57
Network topology 58–59
Neural network (NN) 147, 200
Nonlinear differential equations 139
Normalized difference vegetation index (NDVI) 166
Nvidia Titan X Pascal GPUs 147

One target–one shoot (OTOS) spraying method 114
Open CV 6
Open Systems Interconnect (OSI) model 57–58
Optimal control 40
Orchard management 205–207
  fruit transportation 202–204
  harvesting 199–202
  overview 187–188
  pruning 189–191
  spraying 194–199
  thinning 191–194

OSI. *see* Open Systems Interconnect (OSI) model
OTOS. *see* One target-one shoot (OTOS) spraying method
Output devices 83
Oz Weeder 172

P2M communication. *see* Person-to-machine (P2M) communication
Pan Tilt Unit (PTU) 117, 122, 128
ParallelGPR approach 151
Parallel manipulators 37
Partial differential equations. 139
Partial mixed ration (PMR) 266, 272, 275
Pattern recognition 281
P-code signal 103
Peripheral vision support mechanism 83
Personal Area Network technology 68
Person-to-machine (P2M) communication 60–64, 66–67
Physical layer 57, 58
PID controller. *see* Proportional, integral and derivative (PID) controller
Plant extraction 176
Platform architecture and scalability 89
PlusTech Ltd 243, 246
PMR. *see* Partial mixed ration (PMR)
Pneumatic actuation 202
Polarizing filters 224
Portalharvester 243
Precision agriculture 31, 32–33, 54
Precision farming, nozzles and metering orifice in 32–33
Proportional, integral and derivative (PID) controller 40
Proportional controller 40
PTU. *see* Pan Tilt Unit (PTU)
Pulse width modulation 32

Radio Frequency Identification (RFID) 22, 70–71
RAPID. *see* Robot-assisted precision irrigation delivery (RAPID)
Real Time Kinematics (RTK) 103, 111
Red-green-blue-D (RGB-D) cameras 38, 169, 197, 287, 295
Resistor–capacitor network 10
Responsive behaviour 39
RFID. *see* Radio Frequency Identification (RFID)
RGB-D cameras. *see* Red-green-blue-D (RGB-D) cameras
RGB-D sensor 169, 175, 196–197
RMS. *see* Robotic milking systems (RMS)
Robocrop 173
Robot-assisted precision irrigation delivery (RAPID) 138, 139, 140, 142, 143, 153
  architecture 142–144
  environmental sensing 140
  irrigation scheduling 140–141
  mobile robotics 141
  overview 137–139
  robot task allocation 141–142
  routing algorithms in vineyards 148–152
  soil and field modeling 139–140
  soil moisture inference 144–147
Robot environment/surroundings awareness 90
Robotic arms 37–38
Robotic automation 280
Robotic grippers 42
Robotic milking systems (RMS) 276
  barn design considerations
    cow brushes 264
    cow traffic flow 263–264
    sort pen for cows 265
    split entry fetch pen 264
  feeding management
    composition of pellet 266–267
    grazing herds 267–268
    motivating factor 266
  field observations
    economic considerations 274–275
    feeding cows 270–272
    production 273–274
    quality 272–273
  overview 261–263
  quality and udder health
    challenges 269
    factors influencing 269–270
    mastitis identification 268–269
Robotic poultry harvesting system 287
Robotic sprayer 129–131, 194
  challenges
    control 113
    guidance and mapping 111
    target detection 111–113
  overview 109–111
  in vineyards 113–128
'Robot sheepdog' 22
Robot state awareness 89
Robovator 173
Robust weed control technology 161, 163

Rotary actuators. *see* Hydraulic actuators
RTK. *see* Real Time Kinematics (RTK)
RTK-GPS 60

S-algorithm 152
Sarl Radis weeder 173
Satellite-based internet 15
SBC. *see* Smooth boom control (SBC) system
Scalable vector graphic (SVG) 5
Scale-invariant feature transform (SIFT) 167
SCC. *see* Somatic cell count (SCC)
SDKs. *see* Software development kits (SDKs)
Selective herbicide application systems 171
Selective spraying systems 170–171
Semi-autonomous tractors 52
Semi-rotary motors 30
Serial manipulators 36
SeriesGPR algorithm 151
Shake-and-catch system 200
SICK DX35 13, 15, 117
SIFT. *see* Scale-invariant feature transform (SIFT)
Simultaneous location and mapping (SLAM) algorithms 240
Single-channel NIR cameras 166
SLAM. *see* Simultaneous location and mapping (SLAM) algorithms
Small Unmanned Aerial Systems (sUAS) 55, 64
SMARTAG 52
Smartphone HotSpot 127
Smooth boom control (SBC) system 246
Soft robotic materials 202
Software development kits (SDKs) 196
Soil electroconductivity 140
Soil moisture 140, 143, 144–147
Soil water balance 139
Somatic cell count (SCC) 268, 270, 272–273, 276
Spectral reflectance characteristics 165–167
Spectral shaping 19
Spot spraying systems. *see* Selective spraying systems
's-psi' plot 5, 12
Stepper motor 29, 117
Stereo cameras 290
Stereovision 168, 196
Stress irrigation 138
String thinners 192
sUAS. *see* Small Unmanned Aerial Systems (sUAS)
Supermarket chains 23
Support vector machines (SVM) 144, 201
SUS. *see* System Usability Scale (SUS)
SVG. *see* Scalable vector graphic (SVG)
SVM. *see* Support vector machines (SVM)
'Swarm' machines 23
System Usability Scale (SUS) 90

Target detection 110, 111–113, 120, 122, 127
TCP. *see* Transmission Control Protocol (TCP)
TCP-IP protocol 127
Team orienteering problem (TOP) 148, 151, 152, 190
Tele-manipulation 87
Teleoperation 80, 83, 85, 86, 87, 249
TensorFlow 146
Thread 59
Three-dimensional terrestrial laser scanner 240
Time-of-flight (TOF) sensors 168, 216
TMR. *see* Total mixed ration (TMR)
TOF. *see* Time-of-flight (TOF) sensors
TOF cameras 38
TOP. *see* Team orienteering problem (TOP)
Total mixed ration (TMR) 266, 272
Tractor-mounted systems 32
Transmission Control Protocol (TCP) 57, 58, 66, 69, 70, 72, 127
Transport layer 57
Travelling Salesman Problem (TSP) 201
Tree training systems 189
Trellis systems 189
Triangulation 38
TSP. *see* Travelling Salesman Problem (TSP)
Two-dimensional terrestrial laser scanner 240

UAGVs. *see* Unmanned agricultural ground vehicles (UAGVs)
UAVs. *see* Unmanned aerial vehicles (UAVs)
UDP. *see* User Datagram Protocol (UDP)
UGV. *see* Unmanned ground vehicles (UGV)
UI. *see* User interface (UI)
Ultrasonic sensor 170
Ultraviolet (UV) light 35–36
Universal Mobile Telecommunications Network (UMTS) 61
Universal Robots 171
University of Minnesota 275
University of Wisconsin 270

Unmanned aerial vehicles (UAVs) 141, 164, 193, 198, 240, 244, 252
Unmanned agricultural ground vehicles (UAGVs) 49, 50–55, 60, 62, 64, 66, 68, 69
Unmanned ground vehicles (UGV) 164
US Department of Agriculture 138
User Datagram Protocol (UDP) 57, 58, 66, 69
User interface (UI) 88, 89, 90
US Navstar system 101
UV light. *see* Ultraviolet (UV) light

Vacuum grippers 30–31
Valencian Institute of Agricultural Research (IVIA) 221
Valentini V1500 248
Value optimization algorithms 247
Variable-orifice nozzles 31, 32
Variable-rate application 31, 32
Vegetation pixel segmentation 166, 176
Video systems 4
Virtual Reference Station (VRS) 60–61
Vision-based robot control. *see* Visual servoing
Vision-guided manipulation 38–39
Visual design 89
Visual servoing 38–39
Visual streaming 10
VRS. *see* Virtual Reference Station (VRS)

Waypoint guidance 86
Weed management and control 178–179
  case study 175–177
  challenges
    crop plant perception 164–165
    mechanisms 169–175
  overview 161–164
Weed*Seek*er 170
Wi-Fi 58, 59, 63, 67–68, 72
Wi-Fi Protected Access version 2 (WPA2) 72
WirelessHART 59
Wireless local area networking (WLAN) 59, 61, 63, 68
Wireless networking 51, 54
Wireless sensor networks (WSN) 140
Wireless Wide Area Network 61
WLAN. *see* Wireless local area networking (WLAN)
WPA2. *see* Wi-Fi Protected Access version 2 (WPA2)
WSN. *see* Wireless sensor networks (WSN)

XBee DigiMesh 59
Xbox game 13, 15
X-ray imaging 22

ZigBee 57, 58, 67, 69–70, 72
Z-Wave 59, 67