Chapter 2
Agricultural Robotics for Precision Agriculture Tasks: Concepts and Principles

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This chapter focuses on the principles, conditions and guidelines for agricultural robots to perform precision agricultural tasks, appraises the requirements of robotic systems, and presents associated concepts and characteristics of the complexities and types of precision agricultural tasks from a robotic perspective.

2.1 Introduction

Robots are perceptive machines that can be programmed to perform specific tasks, make decisions and act in real time. They are required in various fields that normally call for reductions in manpower and workload, and are best-suited for applications requiring repeatable accuracy and high yield under stable conditions (Holland and Nof 2007). However, they lack the capability to respond to ill-defined, unknown, changing, and unpredictable events (Moysiadis et al. 2020). Unlike industrial applications, which deal with simple, repetitive, well-defined and predetermined tasks, agricultural applications of automation and robotics require advanced technologies to deal with complex and highly variable environments and produce (Nof 2009). The technical feasibility of agricultural robots for a variety of agricultural tasks has been widely approved. Nevertheless, despite the tremendous amount of research, commercial applications of robots in complex agricultural environments are not yet available (Urrea and Munoz 2015). Such applications of robotics in uncontrolled field environments are still in the developmental stages (Bac et al. 2013). The main limiting factors lie in production inefficiencies and lack of economic justification. Development of an agricultural robot must include the creation of sophisticated,

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intelligent algorithms for sensing, planning and controlling to cope with the difficult, unstructured and dynamic aspects of agriculture (Bechar and Edan 2003).

In agriculture, the environment is very unstructured and demands the motion of robots unlike that of machines in a factory or of vehicles in a parking lot (Canning et al. 2004). It changes in time and space, with environmental conditions considered to be hostile and it requires mobile operation in 3-D changing tracks. The terrain, vegetation, landscape, visibility, illumination and other atmospheric conditions are not well defined; they vary continuously, have inherent uncertainty, and generate unpredictable and dynamic situations (Bechar and Vigneault 2017). Complexity increases when dealing with natural objects, such as fruits and leaves, because of the considerable variation in shape, texture, colour, size, orientation and position that in many cases cannot be determined a priori.

An example of variability in the agricultural environment is presented in Fig. 2.1, illustrating the variation and dynamics of the illumination levels in a bell pepper greenhouse that occur in a few hours and affect the visibility of the rows and the environment. Therefore, the task will require adaptive algorithms that could cope with the rapid changes in time.

From a robotic point of view, the world can be divided into four main domains, according to the structural characteristics of environments and objects: (a) the environment and the objects are structured, (b) the environment is unstructured and the objects are structured, (c) the environment is structured and the objects are unstructured and (d) the environment and objects are unstructured. Each robotic area such as industry, medicine, healthcare, and so on can be associated with one of the domains (Table 2.1). This illustrates the difference between the domains, their complexity and challenges. The agricultural domain is associated with the fourth, in which none

Fig. 2.1 Images of a pepper row in a greenhouse taken from a robotic platform at five different times in a day together with the illumination data (Dar et al. 2011)

Table 2.1 The four robotic domains (a variation on a table from Bechar and Vigneault (2016)

		Environment	
		Structured	Unstructured
Objects	Structured	Industrial/Service domains	Military/Space/Underwater domains
	Unstructured	Medical/Social domains	Agricultural domain

is structured and therefore, it is highly challenging to develop and commercialize. In such environments there are many situations in which autonomous robots fail because of the many unexpected events (Steinfeld 2004). This further complicates the robotic system and results in a system that is difficult and expensive to develop.

Figure 2.2 illustrates the difference in product weight distribution of agriculture and other domains. By quantifying the weight distribution of a specific product population with the coefficient of variation (CV, the standard deviation of the product population weight over the mean of the product population weight), the difference in product weights of different domains can be compared (Bechar and Vitner 2009). The analysis reveals that the CVs are small for metal, plastic and rubber products and vary between 0.01–0.05 and 0.07 to processed wood products. Small CV values represent a narrow population distribution and little variability. However, the CV value of agricultural products, in this case, flower cuttings have CVs that are one to two orders of magnitude larger (CV value of 0.34).

Growing and production processes in agriculture are complex, diverse, require intensive human labour and are usually unique to each crop. The process type and

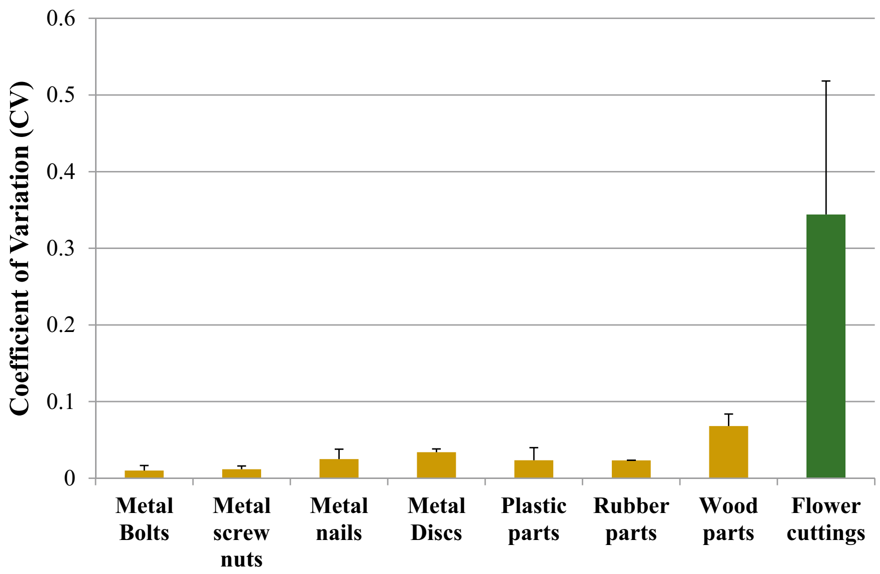

Fig. 2.2 Coefficient of variation (CV) of products in different domains

components are influenced by many factors, including: the crop characteristics and requirements, the geographical or geological environment, climatic and meteorological conditions (Tremblay et al. 2011), market demands, customers' requirements, and the farmer's capabilities and means. The technology, equipment and means that are required for a specific agricultural task involving any given crop and environment will not necessarily be applicable to another crop or in a different environment. The wide variety of agricultural systems and their diversity worldwide make it difficult to generalize the application of automation and control (Schueller 2006), therefore, more efficient agricultural practices are needed.

Agricultural productivity has increased markedly throughout the past 60 years, because of intensification, mechanization and automation. It is an important target for the application of various kinds of technologies designed to improve crop yields and other aspects of farming. In the 20th century, technological progress in developed countries has reduced the manpower for these activities by a factor of 80 (Ceres et al. 1998). Automation increases the productivity of agricultural machinery by increasing efficiency, reliability, quality, uniformity and precision, and reducing the need for human intervention. Although the evolution of technology and the transition to the digitized world of automation has triggered the introduction and use of autonomous robotic systems (Lampridi et al. 2019), one of the main limiting factors in the introduction of robotic systems to agriculture and precision agriculture is the high cost in applying such systems.

Autonomous robots in real-world, dynamic and unstructured environments still yield inadequate results (Bechar 2010), because of inherent uncertainties, unknown operational settings and unpredictable environmental conditions. Inadequacies of sensor technologies further impair the capabilities of autonomous robotics. Therefore, the promise of automatic and efficient autonomous operations has fallen short of expectations in unstructured and complex environments. Complexity increases with the involvement of natural objects, such as those encountered in medical and agricultural environments, because of the considerable variability in shape, texture, colour, size, orientation and position of such objects (Bechar et al. 2009). In addition, the product being dealt with is of relatively low cost, therefore the cost of the automated system must be low for it to be economically justified. Also, the seasonal nature of agriculture makes it difficult to achieve the high degree of utilization found in the manufacturing industries. The complex agricultural environment, combined with intensive production requires robust systems with short development time at low cost (Nof 2009).

The seasonality of agriculture makes it difficult to achieve the high level of utilization found in manufacturing. However, even if the technical and economic feasibility of most of the agricultural robotics applications is not reached in the near future using the existing knowledge and technologies, partial autonomy will add value to the machine long before autonomous robots are fully available. For many tasks, the Pareto principle applies. It claims that roughly 80% of a task is easy to adapt to robotics or automation, but the remaining 20% is difficult (Stentz et al. 2002). Therefore, by automating the easy parts of a task, one can reduce the required manual work by 80%. Furthermore, the development of partially autonomous robots is an excellent transitional path to developing and experimenting with software and hardware elements that will eventually be integrated into fully autonomous systems.

Precision agriculture (PA) was first introduce some four decades ago. The techniques and research in precision agriculture were conducted to align with four main objectives: to increase agricultural productivity, increase produce quality, reduce production costs and reduce environmental impact. Precision agriculture is the main beneficiary of the variability that defines the agricultural domain as discussed above. It aims to exploit the spatial variation using high resolution (up to a single plant level) decision-making and data collection to apply variable-rate operations to increase the total plot revenue and minimize the total cost. We can argue that If not for the variable nature of agriculture, precision agriculture would not be relevant. However, until recently, research in the fields of agricultural robotics and precision agriculture evolved along parallel paths with very little interaction, relation or reference between the two research fields.

Development of an agricultural robot to perform a precision agriculture task must start with development of integrated approaches and operation concepts of both robotics and precision agriculture and include the creation of sophisticated, intelligent algorithms for sensing, planning and control, and decision-making algorithms to cope with the difficult, unstructured and dynamic environment and the unique nature of precision agriculture tasks.

Referring to the three leading characteristics of the agricultural domain: the large degree of variation in the product, the level of structure in the environment and the systems costs, as dimensions in a domination space (Fig. 2.3). The agricultural domain is in the lower right area with high product variability, with poor structure level and low cost demand. It reveals the gaps that needs to be covered and the challenges of robotic systems for agriculture, and for precision agriculture in particular. Robotics is on the other side of the domination space dealing usually with little variation in the product, a well structured level in the environment and relatively large costs. The way to reduce the gap could be by developing concepts and approaches

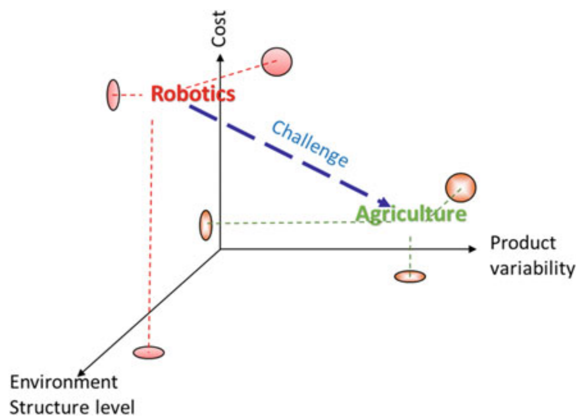

Fig. 2.3 The domination space of the three dimensions: the product variability, the environment structure level in the environment and the cost. The blue line represents the gap robotics will need to cover and the challenges in this area

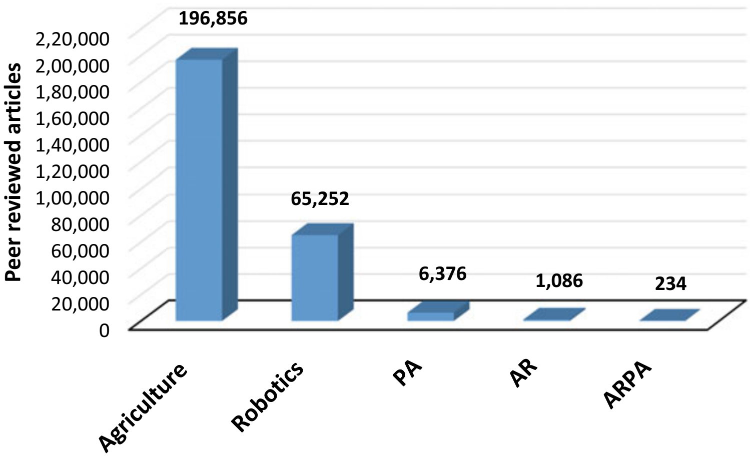

Fig. 2.4 Peer-reviewed articles on the main topic related to agricultural robotics for precision agriculture since 2015. *Source* Scopus, accessed in March 2020. PA—Precision Agriculture, AR—Agricultural Robots, ARPA—Agricultural Robots for Precision Agriculture

that are more suitable for precision agricultural tasks such as focusing on a specific task, and integrating a human operator into the robotic system, simplifying the robotic systems by creating robot teams and so on. These concepts are elaborated in Chaps. 7 and 8.

The relative research effort in the following areas: agriculture, robotics, precision agriculture (including precision farming and precision irrigation), agricultural robotics (AR) and robots for precision agriculture (ARPA) in the past five years is given in Fig. 2.4. It is based on peer-reviewed articles that have been published since 2015 according to Scopus. The annual average increase in the number of articles on PA, AR and ARPA topics is 15%, 20% and 15% respectively, and although 21% of the articles related to agricultural robots (AR) deals with precision agriculture tasks (ARPA), meaning it is an important field to the agricultural robotics community, only 3% of the articles related to precision agriculture topic (PA) were dedicated to agricultural robots.

Analysis of the frequencies of the main keywords in articles related to the ARPA topic revealed the most used keywords. They represent the areas that are investigated and provide an estimate of the directions that interest researchers working on robots for precision agriculture. Figure 2.5 shows the 'normalized frequencies' of the main keywords. 'Normalized frequency' is the number of times that a keyword appears divided by the number of articles on the same topic, i.e., for the keyword 'weed' (with all its derivatives: weed, seeding, etc.), the normalized frequency value is 14.2. This means that on average this keyword appears in 14.2% of the articles related to the ARPA field and probably deal with the precision agriculture task of weed detection, distribution or weeding. Based on this analysis, it seems that the main keywords related to 'agricultural operations' in the ARPA field are weed, harvest,

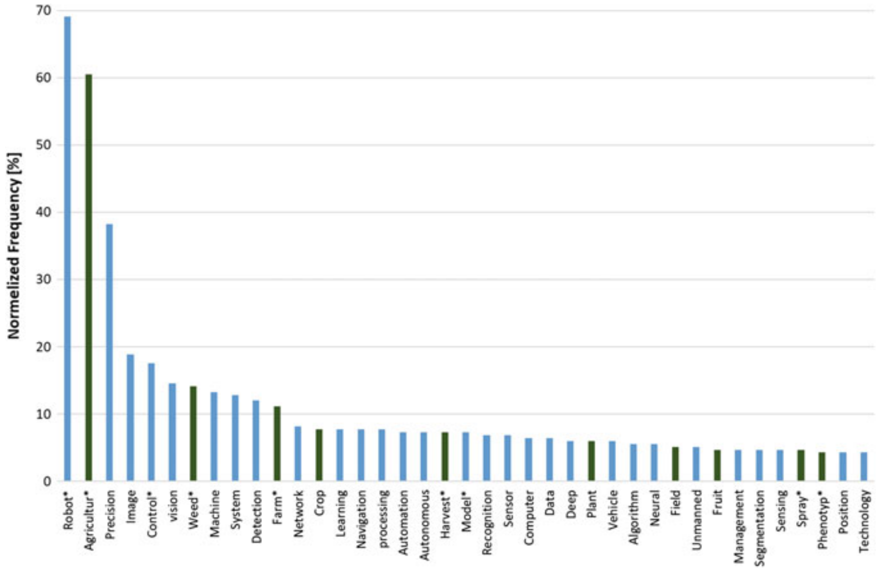

Fig. 2.5 The normalized frequencies of the main keywords used in ARPA articles in the past five years. *Source* Scopus, accessed in March 2020. The green bars represents keywords related to agriculture (crops, operations, etc.). A keyword with an asterisk represents all derivatives of the keyword

fruit, spraying and phenotyping which appear on average in 14.2, 7.3, 4.7, 4.7 and 4.3% of the articles respectively. The keywords related to 'agricultural environment' are farm, field, crop, plant and fruit which appear on average in 11.2, 5.2, 7.7, 6 and 4.7% of the articles respectively.

2.2 Basic Guidelines and Conditions for Applying Robots in Precision Agricultural Tasks

Much research has been carried out on agricultural robotics in the past 40 years. Almost all of them did not reach the commercialization stage. The main causes for incompletion were the extensive costs of the robots developed, inability to execute the required agricultural task, lack of robustness of the system, and inability to reproduce the same task successfully in slightly different contexts or to satisfy operational or economic aspects of the agricultural task. In addition, most approaches were imported from the industrial domain (Vidoni et al. 2015) and did not fit to the tasks in hand. All the effort conducted so far has enabled the formulation of guidelines and definitions of the basic conditions required for development of agricultural robots (Bechar and Vigneault 2016) with modification to precision agriculture. The development and application of robots for precision agricultural tasks has to comply with the following five guidelines:

1. The farmer's requirements for manipulating specific produce must be considered first.
2. The precision agricultural task and its components must be feasible using the existing technology and the required complexity.
3. The required spatial and temporal resolution must be feasible by the robotic system and synchronized with other tasks in the process chain.
4. The cost of the robotic system solution must be less than the expected revenue. It is not necessary that it should be the most profitable alternative.
5. The robotic system developed must have an added value for the performance of the precision agriculture task or for other tasks in that process.

In most cases, the use of robots to perform precision agriculture tasks is achievable if at least one of the following conditions is met:

a. The cost of utilizing robotics is less than the cost of any concurrent methods.
b. The use of robotics enables increasing farm production capability, produce, profit and survivability under competitive market conditions.
c. The use of robotics improves the quality and uniformity of the produce.
d. The use of robotics minimizes the uncertainty and variation in growing and production processes.
e. The use of robotic systems enables the farmer to make decisions and act at greater temporal or spatial resolution compared to the current system to achieve optimization in the growing and production stages in an equivalent manner to 'lean manufacturing' in industry.
f. The use of robotic systems enables an increase in the quality of service or information.
g. The robotic system is able to perform specific tasks that are defined as hazardous or that cannot be performed manually.

2.3 Principles and Classification of Precision Agricultural Tasks for Robotic Applications

Much research has been conducted worldwide in the field of robots for precision agriculture recently (Conesa-Munoz et al. 2015; Bhimanpallewar and Narasingarao 2020; Raja et al. 2020a, b; Sai et al. 2019; Thayer et al. 2020; Ünal et al. 2020). This research has demonstrated the technical feasibility of agricultural robots for a variety of crops, precision agriculture tasks and robotic abilities. However, automation solutions have not yet been commercially implemented successfully for field operations and only a few developments have been adopted and put into practice (Xiang et al. 2014). Incompatibility between the robotic system designed and the precision agriculture task led to production inefficiencies, long cycle times and delays, low detection rates (Zhao et al. 2016) and the inability to perform the necessary PA tasks satisfactorily. The unstructured nature of agricultural environments generates stochastic task requirements and the live and fragile plant and produce make features of the agricultural task quite different from industrial applications that work with inorganic products.

Robots for precision agriculture tasks comprise numerous sub-systems and devices that enable them to operate and perform their tasks. These sub-systems and devices deal with path planning, navigation or guidance abilities (Carpio et al. 2020, Zaidner and Shapiro 2016), mobility, steering and control (Lipinski et al. 2016), sensing, manipulators or similar functional devices (Mann et al. 2014), end effectors, control, decision-support systems to manage individual or simultaneous unexpected events, and some level of autonomy (van Henten et al. 2013). Robots for precision agriculture are generally designed to execute a specific agricultural task, such as specific spraying (Asaei et al. 2019), selective weeding (Wu et al. 2020b), disease monitoring (Kerkech et al. 2020, Liang et al. 2020), selective pruning (Bechar et al. 2014), and so on. These are considered to be the 'main tasks' to be performed by the robotic system. To execute the 'main task' successfully, the robotic system must perform several 'supporting tasks', such as localization and navigation, detection of the object to treat, etc. Information and commands are transferred between the 'supporting tasks' and the 'main task'. Each 'supporting task' controls one or several sub-systems and devices, and a sub-system or device may serve several 'supporting tasks' (Fig. 2.6). For instance, in developing a disease monitoring robot (Schor et al. 2016a), the 'main task' is disease monitoring, the robotic system needs to be able to perform the 'supporting tasks' of self-localization, trajectory planning, steering and

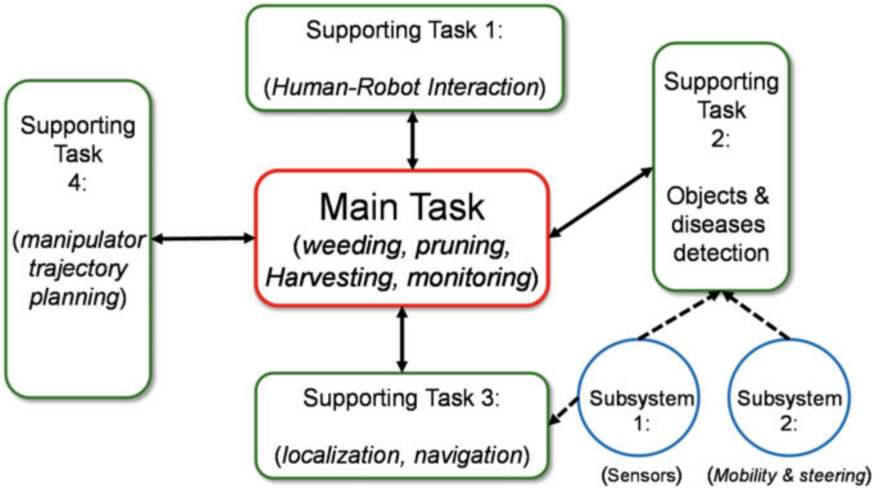

Fig. 2.6 Structure of task sub-systems in an agricultural robot. Solid arrows represent commands, data and information transfer; dashed arrows represent conceptual connections. The writing in the parentheses are examples for agricultural robot 'main tasks', 'supporting tasks' and subsystems (Bechar and Vigneault 2016)

navigating in the plot from its actual location to the next sampling location, collaborating with a human operator or interacting with a human presence, other robots or unexpected objects on the path and to modify its trajectory planning as necessary. Nguyen et al. (2013) developed and implemented a framework for motion and hierarchical task planning for an apple harvesting robot, Bechar et al. (2009) developed a methodology for melon detection by a human–robot system to be used by a melon harvesting robot and Ceres et al. (1998) developed and implemented a framework for a human integrated citrus harvesting robot. A framework for agricultural and forestry robots was developed by Hellstrom and Ringdahl (2013).

Further investigation of the precision agriculture task characteristics, i.e. the 'main task' to execute in the robotic framework, reveals that it can be classified into a three-level scale based on the task complexity. The task complexity can be defined by the level of robot–plant interaction, whereas higher level represents greater challenges. The lower level of complexity of the robot–plant interaction requires no physical contact between the robot and the plant. At this level, the precision agriculture tasks are involved mainly in (i) data collection using visual and other sensors (elaborated in Chap. 3), e.g. early detection of diseases and pests, abiotic stress diagnostics and identification of anomalies (Sanchez et al. 2020; Freitas et al. 2020), (ii) transportation of produce, materials and tools between different locations of the farm (Guzman et al. 2016) and (iii) remote material application such as variable-rate fertilizer application, selective and specific spraying, and so on (see more in Chap. 6). The middle level of complexity requires physical contact between the robot and the plant but no handling of produce, materials or plant parts. Typical precision agriculture tasks at this level are selective mechanical weeding (Tillett et al. 2008) that will physically damage the weed but does not collect or handle it, seedling, fruit thinning, and branch pruning that removes fruitlets and branches, etc. The third level of complexity of the robot–plant interaction and the most challenging one requires both physical contact between the robot and the plant and handling of produce, materials or plant parts. Among the tasks at this complexity level would be fruit picking, harvesting of leaf crops, which require precise operation, decision-making and handling the produce without impairing it or reducing its quality. Transplanting of plants and trees, transferring of pots (with plants) in plant nurseries, and so on.

In addition, since the main objectives of precision agriculture tasks are either to collect data, analyse it, make decisions or act accordingly at a higher resolution, up to the plant level, precision agriculture tasks can be defined and classified according to three phases or stages concerning the operation of agricultural robots in executing the 'main task'. The first stage of a PA 'main task' deals with data collection. Representative tasks in this stage are high spatial and temporal resolution monitoring of climate and environmental conditions, soil sampling (Lukowska et al. 2019; Schnug et al. 1998) for nutrients, pests and bacteria, visual and acoustic monitoring (Finkelshtain et al. 2017; Schor et al. 2016b) of anomalies, biotic and abiotic stresses (Wang et al. 2019), yield and plant conditions. The second stage is attributed to decision-making, optimization and decision-support processes. Characterizing PA tasks at this stage are irrigation management interfaces, classification tasks, planning of farm processes and so on. The third stage relates to tasks that require action or

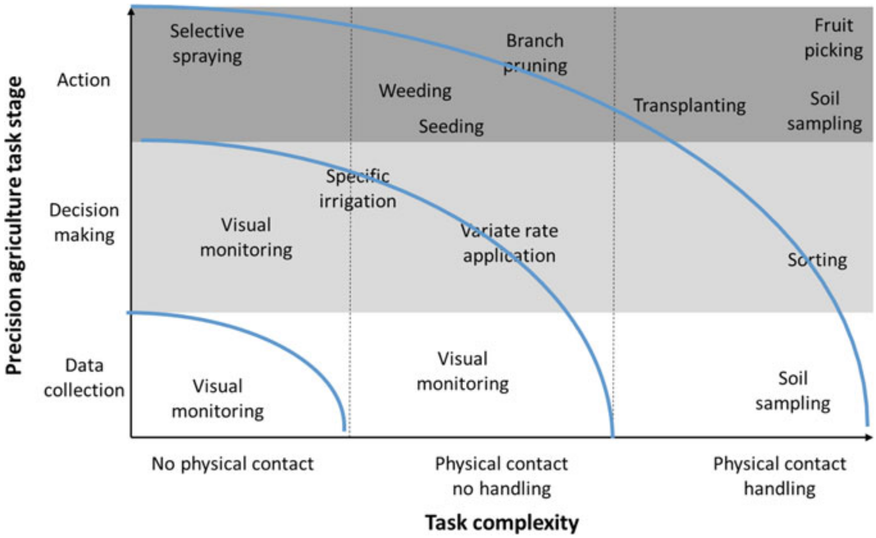

Fig. 2.7 The precision agriculture task classification space based on the task complexity level and the precision agriculture stage. The location of several different tasks in this space can demonstrate the challenge level. The blue lines represent equal level values of challenges and research and development effort of robotics in performing a precision agricultural task

physical performance such as specific spraying, transplanting and seeding (Gao et al. 2016; Bhimanpallewar and Narasingarao 2020), weed control (Wu et al. 2020a; Raja et al. 2020a), fruit picking and harvesting (Bloch et al. 2018), etc.

Combining the two classifications of precision agriculture tasks discussed above and creating a task classification space (Fig. 2.7), can enable us to position a specific task and to estimate the challenge level, and the required research and development effort in designing a robot to perform that task (Fig. 2.7). In this analysis the two classification dimensions have a similar influence on the challenge level. The challenge level of a specific task can be evaluated qualitatively by the magnitude of the distance between the task location to the origin of the axes.

2.4 Conclusions

Research, developments and evaluations of robots to perform precision agriculture tasks are very diverse in terms of objectives, structures, techniques and components. In this context, it is difficult to compare different robots and to transfer developed technology from one task to another. The limiting factors for the development of such systems are unique to each robotic system and precision agriculture task. In this chapter, an investigation of the characteristics of precision agriculture tasks was conducted and an evaluation platform between different systems and tasks was created.

Research and development of robotic systems to perform precision agriculture tasks need to follow several steps. First, investigate and study the nature of the task, the process and the environment in relation to variation in the leading variables to evaluate the feasibility of the suggested solution. Second, technologies and methodologies must be developed or modified to fit high variable situations and to overcome difficult problems such as the continuously changing conditions, the variability of the produce and the environment, and hostile environmental conditions such as vibration, dust, extreme temperature and humidity. Third, Identification of processes or tasks that can be 'robotized', evaluation of the overall task complexity and the precision agriculture stage. Fourth, evaluation of the challenge level and the required research and development effort for such a system and tasks. For very complex tasks, a high challenge level or large research and development effort, possible solutions to overcoming this problem might be agronomic modifications or a human integration. Fifth, to investigate if the solution presented complies with the guidelines and conditions discussed in Sect. 2.2. Finally, agricultural robotic systems should be developed only from tasks and processes where other solutions, such as mechanics or automation, cannot exist or that robotics has a diminishing marginal utility with use of them.

The robots that are to be used for precision agriculture tasks must recognize and understand the physical properties of each specific object, and must be able to work under different and dynamic environmental conditions in fields, or in controlled environments. Therefore, they need sensing systems that can work under variable conditions, as well as specialized manipulators and end-effectors. The environmental conditions are occasionally so severe with regard to high temperature, humidity, dust and or rain that electrical circuit and material corrosion problems can be a major concern. These conditions must be taken into consideration when designing robotic systems for precision agriculture tasks. In this sense, development and application of robots for precision agriculture tasks is an iterative process.

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