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1 Introduction

Agriculture is the "science, art, or practice of cultivating the soil, producing crops, and raising livestock and in varying degrees the preparation and marketing of the resulting products" (1). The term "*agricultural robots*" is commonly used to refer to mobile robotic machines that support or perform agricultural production activities. Although some robots have been developed for forestry, animal production and aquaculture (2, 3, 4, 5, 6, 7) the large majority of agricultural robots has been, and is being, developed for crops. Hence, the scope of this article is restricted to agricultural robots for crop production, and more specifically to ground robots participating in open field operations that range from plant breeding to crop establishment, cultivation and harvest. Post-harvest processing has been traditionally served by "hard automation" technologies, although mechatronics and robotics are increasingly becoming part of post-harvest and food manufacturing systems (8).

The rapid growth of interest, investment and research in agricultural robotics has been driven by two main challenges that 21st century agriculture faces.

1.1 Challenge #1: Sustainable growth of agricultural production

We must significantly *increase the production* of consumer-safe, high-quality food, feed, fiber and biofuel products to cover the needs of an increasing world population that has more purchasing power and affluence, and ensuing per capita consumption. This must be accomplished in an economically and environmentally *sustainable* fashion that conserves the resource base, including (agro) biodiversity, water, and soil, despite limitations in arable land and fresh water resources.

On the cultivation side, agricultural robotics technologies are essential in achieving this goal by providing mobile sensing, computation and actuation that enable *precision farming* (apply the right types and amounts of inputs, at the right time, at the right place) at ever - increasing spatial and temporal resolutions, even *at individual plant level*. Such selective, individual plant care systems have been called "phytotechnology" (from ancient Greek *φυτόν* (phutón, "plant") (9) and hold great potential for maximizing production while minimizing water, chemical and energy inputs.

On the breeding side, fast development of radically improved crop varieties (highly productive, draught and disease tolerant) will rely on our ability to functionally link – to model and predict – the plant phenotype (observable characteristics such as height, biomass, yield, et., and their evolutions over time) as the result of the interactions of genotype, field environment, and crop management. This is the challenging task of *field phenomics* or *phenotyping*, i.e., the automated, high–throughput, proximal, non–destructive measurement of plants' phenotypes in fields. "Breeding is essentially a numbers game: the more crosses and environments used for selection, the greater the probability of identifying superior variation" (10). Agricultural robots can offer the mobility, advanced sensing and physical sampling required for high-throughput field phenotyping.

1.2 Challenge #2: Addressing farm labor shortages

In the past decades, farmers, and in particular fruit, vegetable and horticultural farmers have relied on hired, low-wage workers, especially during the harvest periods. Recent studies indicate that as a result of socioeconomic, structural and political factors, local and migrant farm labor supply cannot keep up with demand in many parts of the world (11, 12). Also, due to increasing industrialization and urbanization large countries like China are already moving towards the Lewis turning point, where surplus rural labor reaches a financial zero (13); China is expected to reach it between 2020 and 2025 (14). Agricultural robots hold the potential to remedy existing and imminent farm labor shortages by increasing worker efficiency and safety acting as *co-bots* interacting with workers (e.g., harvest-aids), or by replacing workers in low-skill, labor-intensive tasks, like manual weeding or fruit and vegetable harvesting.

1.3 Agricultural robots

Many agricultural (ground) robots have been developed to perform precision farming operations and replace or augment humans in certain tasks. These robots come in two main types: I) self-propelled mobile robots, and II) robotic "smart" implements that are carried by a vehicle. Type-I robots span wide ranges of sizes and designs. Conventional agricultural self-propelled machines such as tractors, sprayers, and combine harvesters have been "robotized" over the last decade through the introduction of GPS/GNSS auto-guidance systems. These machines are commercially available today and constitute the large majority of "agricultural robots". They can drive autonomously in parallel rows inside fields while a human operator supervises and performs cultivation-related tasks; turn autonomously at field headlands to enter the next row; and coordinate their operations (e.g., harvester unloading) (Figure 1a). Autonomous *cabinless* general purpose 'tractor robots' were recently introduced by several companies that are compatible with standard cultivation implements (Figure 1b) (Figure 1c). These larger robots are designed primarily for arable farming related operations that require higher power and throughput, such as ploughing, multi-row seeding, fertilizing, and spraying, harvesting and transporting.

A large number of smaller type-I special purpose mobile robots have also been introduced for lower-power applications such as scouting and weeding (Figure 1d) of a smaller number of rows at a time. Most of these robots are research prototypes introduced by various research groups. A few commercial or near-commercial mobile robots have emerged in applications like container handling in nurseries (Figure 1f) and seeding (Xaver - Figure 1e), respectively. Small robots like Xaver are envisioned to operate in teams and are an example of a proposed paradigm shift in the agricultural machinery industry, which is to utilize teams of small lightweight robots to replace large and heavy machines, primarily to reduce soil compaction.

Figure 1 a) Auto-steered harvester and fully autonomous tractor pulling a grain cart for harvester unloading (Photo courtesy of Kinze Manufacturing/PrecisionAg.com); b) Cabinless fully autonomous general purpose tractor (CASE IH) and c) Robotti - AGROINTELLI, Denmark; d) Bonirob-Picture: Bosch; e) Autonomous robot seeder (Fendt – AGCO GmbH); f) Nursery robot for moving containers (Harvest Automation, USA).

Type-II robots ("smart" implements) have been developed for various applications, and some are already commercially available, in applications like transplanting, lettuce thinning (Figure 2a) and mechanical weeding (Figure 2b). Robotic implements at pre-commercial stage are also developed for applications like fruit harvesting (Figure 2c) and vine pruning (Figure 1d) in orchards and vineyards, respectively. Other orchard operations such as flower and green fruit thinning to control crop load have also been targeted for automation.

Figure 2 a) Lettuce thinning robotic implement (Blue River – NSF photo archive); b) Robotic mechanical weeder (courtesy of Steve Fennimore); c) Operators of an Abundant Robotics automated vacuum harvester monitor the test vehicle working a Fuji apple block during the 2016 Washington apple harvest. (TJ Mullinax/Good Fruit Grower); d) Robotic vine pruner (Vision Robotics).

1.4 Article scope and structure

Recent review articles have discussed some of the opportunities and challenges for agricultural robots and analyzed their functional sub-systems (15); summarized reported research grouped by application type (e.g., seeding weeding) and suggested performance measures for evaluation (16); and presented a large number of examples of applications of robotics in the agricultural and forestry domains and highlighted existing challenges (17).

The goals of this article are to: 1) highlight the distinctive issues, requirements and challenges that operating in agricultural production environments imposes on the navigation, sensing and actuation functions of agricultural robots; 2) present existing approaches for implementing these functions on agricultural robots and their relationships with methods from other areas such as field or service robotics; 3) identify limitations of these approaches and discuss possible future directions for overcoming them.

The rest of the article is organized as follows. The next section discusses autonomous navigation (including sensing), as it is the cornerstone capability for many agricultural robotics tasks. Afterwards, sensing relating to crop and growing environment is discussed, where the focus is on assessing information about the crop and its environment in order to act upon it. Finally, interaction (actuation) with the crop and its environment is discussed, followed by summary and conclusions.

2 Autonomous navigation

In this work the term “autonomous navigation” encompasses the computation and execution of the necessary motions of an autonomous agricultural vehicle so that the task-specific actuation or sensing system covers all targeted crops in the designated cultivation area. In general, navigation in the agricultural domain involves the following operations:

1. Field layout planning: compute the spatial layout for crop row establishment.
2. Vehicle route planning: compute row traversal sequence and vehicle cooperation logistics.

3. Vehicle Motion planning: compute path and motion profiles.
4. Vehicle auto-guidance: perform sensing, perception and control to execute a motion plan.

Clearly, the first three operations are not independent. For example, the spatial arrangement of field rows and row-traversal sequence that minimize working time depend not only on field geometry and row spacing, but also on vehicle mobility and maneuvering during turning at headlands to switch rows. The prevailing approach has been to assume obstacle-free headlands and use geometric approximations of headland maneuvering costs derived analytically - rather than numerically - to solve problems #1 or #2 independently, or combined. In the general robotics literature the combined problem is referred to as *coverage path planning* (18).

An emerging idea in agricultural robotics is the utilization of teams of small autonomous machines to replace large machines (9). In such scenarios, routing, motion planning and auto-guidance approaches must be extended to multiple robots. When these machines operate in parallel but independently the extensions deal mostly with splitting the field (workload) and avoiding collisions. However, when machines collaborate, as for example combine harvesters and unloading service trucks do during harvesting, issues of coordination, scheduling and dispatching need to be addressed. This scenario is also known as *field logistics* and will be covered as part of vehicle routing.

2.1 Field layout planning

Given a field geometry this operation essentially computes a good way to drive over a field in order to establish (till, plant) and then cultivate the crop. This step is necessary only for annual open field crops.

2.1.1 Agricultural domain background

The operation computes a complete spatial coverage of the field with geometric primitives (and their connectivity) that are compatible with and sufficient for the task, and optimal in some sense. Headland space for maneuvering must also be generated. Agricultural fields can have complex, non-convex shapes, with non-cultivated pieces of land inside them. Fields of complex geometry should not be traversed with a single orientation; the efficiency would be too low because of excessive turning. Also, fields are not necessarily polygonal, they may have curved boundaries and may not be flat. Additionally, most agricultural machines are non-holonomic and may carry a trailer/implement, which makes computing turning cost between swaths non trivial (turning cost is used as part of field layout ranking). Finally, agricultural fields are not always flat and field traversal must take into account slope and vehicle stability and constraints such as soil erosion and compaction.

2.1.2 Existing approaches

Computing a complete spatial coverage of a field with geometric primitives is in principle equivalent to solving an exact cellular decomposition problem (19). A recent review of coverage approaches can be found in Galceran and Carreras (18). Choset and Pignon, (20) developed the *Boustrophedon* cellular decomposition (in Greek it means "the way the ox drags a plough"). This approach splits the area into polygonal cells that can be covered exactly by linear back-and-forth motions. Since crops are planted in rows, this approach has been adopted by most researchers. A common approach is to split complex fields into simpler convex subfields (aka regions, blocks, plots) via a line sweeping method, and compute the optimal driving direction and headland arrangement for each subfield using an appropriate cost function that encodes vehicle maneuvering in obstacle-free headland space (21, 22, 23). This approach has been extended for 3D terrain (24, 25).

2.1.3 Limitations and possible directions

Existing approaches assume that headland space is free of obstacles and block rows are traversed consecutively, i.e., there is no row-skipping. These are simplifying assumption, as it has been shown that proper row sequences reduce total turning time substantially (26). However, dropping this assumption would require solving a routing optimization problem inside the loop that iterates through driving orientations, and many maneuvering/turning motion planning problems inside each route optimization; this would be very expensive computationally. Furthermore, all algorithms use a swath of fixed width, implicitly assuming that the field will be covered by one machine, or many machines with the same operating width. Relaxing this assumption has not been pursued, but the problem would become much more complicated. Planning could also be extended to non-straight driving patterns (e.g., circular ones in center pivots) using nonlinear boustrophedon decompositions based on Morse functions (27), with appropriate agronomic, cultivation and machine constraints.

Finally, as pointed out by Blackmore (9), row cultivation was historically established because it is easier to achieve with animals and simple machines. Crops do better when each plant has equal access to light, water and nutrients. Small robots could *grow crops in grid patterns* with equal space all around by following arbitrary driving patterns that may be optimal for the cropping system and the terrain. Hence the boustrophedon assumption could be relaxed and *approximate cellular decomposition* could be used to compute optimal driving patterns, where field shape is approximated by a fine grid of square or hexagonal cells. This approach has received very little attention, as field spatial planning has targeted existing large machines. An example of early work in this direction *combined route planning and motion planning*, with appropriate agronomic, cultivation and machine constraints (28).

2.2 Vehicle route planning

Given a field decomposition and a set of locations/waypoints outside the field where logistics support is provided (e.g. sprayer re-filling), this operation computes an optimal traversal sequence to drive through all primitives, utilizing the appropriate waypoints to enter and exit each primitive and perform logistics. The operation is necessary for robot deployment in all agricultural settings (row crops, orchards, greenhouses). A related task is that of visiting a set of known, pre-defined field locations in order to take measurements, samples (e.g., soil or plant tissue), collect bale, etc.

2.2.1 Agricultural domain background

The basic version of route planning computes an optimal traversal sequence for the field rows that cover the field, for a single auto-guided machine with no capacity constraints. This is applicable to operations in arable land, orchards and greenhouses that do not involve material transfer (e.g., ploughing, mowing, scouting) or, when they do, the quantities involved are smaller than the machine's tank or storage space; hence the machine's limited storage capacity does not affect the solution. For operations where the machine must apply or gather material in the field (e.g., harvesting, fertilizing, spraying) the maximum number of rows it can cover is restricted by its capacity; the same applies to fuel. Hence, route planning with capacity constraints is a more complicated version of the problem.

When many machines operate in the same field there are two classes of operations which have different characteristics. The first class is when *machines are independent of each other*, i.e., they do not share any resources. In such cases, coordinated route planning is straightforward because the machines can simply work on different swaths or subfields of the field; possible crossings of their paths at the headlands and potential collisions can be resolved during task execution. The second class is *cooperative field operations*, also known as *in-field logistics*, which are executed by one or more primary unit/s performing the main task and one or more service unit/s supporting it/them. For example, in a harvesting operation a self-propelled harvester may be supported by transport wagons used for out-of-the field removal of harvested grain (Figure 1a). Similarly, in fertilizing or spraying operations the auto-guided spreader/sprayer may be supported by transport robots carrying the fertilizer/sprayer for the refilling of the application unit.

Agricultural tasks are dynamic and stochastic in nature. The major issues with off-line route planning are that it breaks down in case of unexpected events during operations, and it can only be performed if the "demand" of each row is known exactly in advance. For example, if a sprayer's flow rate is constant or the crop yield is known in advance, the quantity of chemical or harvest yield ("demand") of each field row can be pre-computed and optimal routing can be determined. However, yield maps are either not available before harvest or their predicted estimates based on sampling or historic data contain uncertainty. Also, robotic precision spraying and fertilizing operations are often performed "on-the go" using sensors, rather than relying on a pre-existing application map. Hence, information is often revealed in a dynamic manner during the execution of the task.

2.2.2 Existing approaches

Vehicle routing for agricultural vehicles is based on approaches from operations research and transportation science. Optimal row traversal for a single or multiple independent auto-guided vehicles has been modeled and solved as a Vehicle Routing Problem (26, 29, 30, 31). This methodology was conceptually extended (32) to include multiple identical collaborating capacity-limited machines with time-window (synchronization) constraints, and to non-identical vehicles (33). A review of similar problems in transportation science is given in (34).

The problem of visiting a set of known, pre-defined field locations to take measurements or samples is not an area coverage problem, and was recently modeled as an orienteering problem (Thayer et al., 2018) for non-collaborating robots, and as VRP with time-windows for capacitated cooperating vehicles (36).

Dynamic, on-line route planning has recently received attention in the agricultural robotics literature for large-scale harvesting operations (wheat, corn, sugarcane) because of its economic importance and the availability of auto-guided harvesters and unloading trucks. Reported approaches compute a nominal routing plan for the harvesters assuming some initial yield map, and then they route the support units based on the computed points where harvesters fill up their tanks (37, 38). The plan is adjusted during operations based on updated predictions of when and where harvester tanks will be full. A recent application that falls in this category is robot-aided harvesting of manually harvested fruits (39), where a team of robotic carts transports the harvested crops from pickers to unloading stations, so that pickers spend less time walking.

Overall, the increasing deployment of commercially available auto-guided harvesters and unloading trucks, and the emerging paradigm of replacing large, heavy machines with teams of smaller agricultural autonomous vehicles (40) drive the need for practical on-line route planning software.

2.2.3 Limitations and possible directions

Primary units (harvesters, sprayers, human pickers, etc.) and support autonomous vehicles form a ‘closed-loop’ system: the delays introduced by the support vehicles affect the primary units’ temporal and spatial distributions of future service requests. Reactive policies (go to a harvester when its tank is full) are not efficient enough, because support trucks/robots must traverse large distances to reach the primary units in the field, thus introducing large waiting times. The agricultural vehicle routing (or in-field logistics) problem lies under the broad category of Stochastic Dynamic VRP (SDVRP) (41). The incorporation of *predictions* about future service requests (by primary units) has been shown to improve scheduling for SDVRP (42). However, most SDVRP applications (e.g. fuel transportation, inventories replenishment) are characterized by requests that are stochastic and dynamic in time, but fixed and known in terms of location (43). In contrast, service requests from primary units in agriculture are stochastic and dynamic, both temporally and spatially (44). Also, the real-time and dynamic nature of agricultural operations means that very few established requests are available to the planner/scheduler, which has to rely much more on predicted requests. In addition, the optimization objective also varies depending on the situation. For example, it can be minimizing waiting time, maximizing served requests and so on, while VRP mainly focuses on minimizing travel distance. Therefore, existing SDVRP predictive scheduling approaches are not well suited for agriculture and more research is needed to incorporate uncertainty in on-line route planning for teams of cooperating autonomous agricultural machines.

2.3 Motion planning

Once vehicle routing has generated waypoints sequences for the robots to visit, this operation computes paths and associated motion profiles to move between and transition at waypoints.

2.3.1 Agricultural domain background

Agricultural robots will typically execute computed motions for a very large number of times (e.g., headland turn maneuvers). Therefore particular focus has been on computing paths and trajectories that are optimal in some economic or agronomic sense. Also, in most cases vehicles are non-holonomic. The general problem of moving a vehicle from one point/pose to another (e.g., between orchard blocks or from the field to a silo) lies in the area of general motion planning and is covered adequately in the robotics literature (45). The focus of this section is on motion planning inside field or orchard blocks. When several machines operate independently of each other in the field they do not share resources, other than the physical area they work in. Furthermore, independent robots will typically operate in different field or orchard rows and their paths may only intersect in headland areas, which are used for maneuvering from one row to the next. Therefore, motion planning is restricted to *headland turning* and involves: a) planning of independent geometrical paths for turning, and b) computing appropriate velocity profiles for these paths so that collision avoidance is achieved, when two or more robot paths intersect. Problem (b) is a coordinated trajectory planning problem and has been addressed in the robotics literature (46). In headlands, *optimal motion planning* is of particular interest, as turning maneuvers are non-productive and require time and fuel.

2.3.2 Existing approaches

Approaches to automatically compute optimal headland turning trajectories in the absence of obstacles include optimal control (47), analytical calculations with parametric curves (48), and numerical integration of vehicle kinematics (49, 50).

2.3.3 Limitations and possible directions

The computation (and execution) of headland turning maneuvers in the absence of obstacles has matured to a point where it is available as part of commercial auto-guidance products (e.g., CASE IH's AccuTurn™, John Deere's AutoTrac™ Turn Automation, Fendt's Variotronic^{TI} Turn Assistant, Topcon's Horizon auto-turn). Computing optimal headland maneuvers in the presence of obstacles is still a challenging problem and this capability is not offered in commercial navigation packages. Agriculture-targeted approaches based on A^* search in configuration space (51) and random search followed by optimization (52) have been adapted from the general robotics literature, which has investigated the problem extensively (45); further research can capitalize on state-of-the-art methods, with an emphasis on completeness and robustness.

2.4 GNSS-based guidance

Auto-guided agricultural vehicles must be able to perform two basic navigation tasks: follow a row, and maneuver to enter another row. The latter requires detection of the end of the current row and the beginning of the next row. The route planning layer specifies the sequence of row traversal and the motion planning layer computes the nominal paths.

During row following, precision crop cultivation requires precise and repeatable control of the vehicle's pose (and its implement/actuators/sensor) with respect to the crop. Inside rows, agricultural vehicles travel at various ground speeds, depending on the task. For example, self-propelled orchard harvesting platforms move as slow as 1-2 cm/s; tractors performing tillage operations with their implement attached and their power take off (PTO) engaged may travel at 1 Km/h up to 5 Km/h. Sprayers may travel at speeds ranging from 8 Km/h up to 25 Km/h. Vehicle working speeds in orchards are typically less than 10 Km/h. The above speeds are for straight or slightly curved paths; during turning maneuvers much slower ground speeds are used. Wheel slippage is common during travel, especially in uneven or muddy terrain. Also, agricultural vehicles will often carry a trailer or pull an implement, which can introduce significant disturbance forces.

There are two basic auto-guidance modes: absolute and crop-relative (53) (and, of course, their combination). *Absolute auto-guidance* relies exclusively on absolute robot localization, i.e., real-time access to the geographical coordinates of the vehicle's location, its absolute roll, pitch and yaw/heading, and time derivatives of them. These components of the vehicle's state are estimated based on GNSS and Inertial Navigation System (INS). Tractor GPS-based absolute auto-guidance was first reported in 1996 (54), after Carrier Phase Differential GPS technology became available. Since then, auto-guidance (aka auto-steering) for farming using Global Navigation Satellite Systems (GNSS) has matured into commercial technology that can guide tractors - and their large drawn implements - with centimeter-level accuracy, on 3D terrain, when Real Time Kinematic (RTK) corrections are used. Absolute guidance can be used for precision operations when there is an accurate georeferenced map of the field and crop rows that is valid during operations, and the vehicle knows its exact position and heading in this map, in real-time. Essentially, establishing accurate vehicle positioning with respect to the crop is achieved by achieving absolute machine positioning on the map. The first step towards this approach is to use RTK GPS guided machines to establish the crop rows – and their map (e.g., seeding (55, 56), transplanting (57). After crop establishment, as long as crop growth does not interfere with driving, vehicles can use the established map to repeatedly drive on the furrows between rows using RTK GPS (58, 59).

Accurate, robust and repeatable *path tracking control* is needed for precision guidance. The topic has received significant attention in the literature with emphasis given on slip compensation and control of tractor-trailer systems. Approaches reported in the literature include pure-pursuit (60), side-slip estimation and compensation with model based Liapunov control (61), backstepping predictive control (62), fuzzy neural control (63), sliding mode control (64), and others. Model-based approaches have also been proposed, such as non-linear model predictive control (65, 66), and robust nonlinear model predictive control (67).

Absolute auto-guidance is an established commercially available technology that has acted as enabler for many precision agriculture technologies for row crops, such as variable rate application of seeds and chemicals. It has also led to recent advances in field automation, including the development of remotely supervised autonomous tractors without cabin (e.g., Case IH Autonomous Concept Vehicle) and master-slave operation of grain carts with combines for autonomous harvesting systems (e.g., Kinze Manufacturing, Inc.).

Absolute auto-guidance is not practical in row crops or orchards where one or more of the following are true: a) no accurate crop rows map is available to be used for guidance because crop establishment was performed with machines without RTK GPS; b) such a map exists but changes in the environment or crop geometries may render pre-planned paths non collision-free (e.g., larger tree growth on one side of an orchard row necessitates deviation from the straight line); c) GNSS is inaccurate, unreliable or unavailable (e.g., large positioning error due to vegetation-induced multipath or signal blockage). In these operations plants grow in distinct rows and the wheels of the autonomous vehicles must drive only inside the space between rows. Examples include open field row crops (e.g., sugar beet); orchards with trees/vines/shrubs and their support structures; greenhouses and indoor farms.

Crop-relative auto-guidance is necessary in the situations described above. Researchers have used various sensors, such as onboard cameras and laser scanners to extract features from the crops themselves, and use them to localize the robot relative to the crop lines or trees rows in order to auto-steer. Crop-relative guidance in open fields and orchards is still more of a research endeavor rather than mature, commercial technology.

2.5 Crop-relative guidance in open fields

Most of the work so far has focused on row detection and following, and in particular on the estimation of the robot's offset and heading relative to middle line of the row between the crop lines. All approaches exploit the fact that multiple parallel crop lines are spaced at known and relatively fixed distances from each other. Although the problem of finding such crop rows in images may seem straightforward, real-world conditions introduce complications and challenges that will be discussed next.

2.5.1 Agricultural domain background

When the crop is visually or spectrally different from the material inside furrows (soil), discrimination between soil and crop is easy (Figure 3 a). However, it can be very challenging in the presence of intra-row (in the furrows) weeds (Figure 3 b) or when there are cover crops or intercropping in the furrows (Figure 3 c), as the visual appearance of the intra-row plants can have similar visual and spectral characteristics to the crops in the rows that need to be detected. Other challenges include row detection of different plant types at various crop growth stages, variability in illumination conditions during daytime or nighttime operation, and environmental conditions (e.g., dust, fog) that affect sensing. Robustness and accuracy are very important features for such algorithms, as erroneous line calculations can cause the robot to drive over crops and cause economic damage.

Figure 3 a) Lettuce, Salinas, CA, USA (BrendelSignature at English Wikipedia; b) sugarbeet with weeds (Sidi Smaïl, Morocco, Wikipedia; c) strawberries with cover crops inside furrows (Maryland, USA, Wikipedia)

2.5.2 Existing approaches

Researchers have used monocular cameras in the visible (RGB) (68, 69) or near infrared (NIR) spectrum (70, 71), or multiple spectra (72, 73) to *segment* crop rows from soil based on various color transformations (74) and greenness indices (75) that aimed at increasing segmentation robustness against variations in luminance due to lighting conditions. Recently, U-Nets (76), a version of Fully Convolutional Networks (FCNs) were used to segment straw rows in images in real-time (77).

Other approaches do not rely on segmentation but rather exploit the a priori knowledge of the row spacing, either in the spatial frequency domain - using bandpass filters to extract all rows at once - (78, 79) or in the image domain (80). An extension of this approach models the crop as a planar parallel *texture*. It does not identify crop rows per se, but computes the offset and heading of the robot with respect to the crop lines (81).

Once candidate crop row pixels have been identified various methods have been used to fit lines through them. Linear regression has been used, where the pixels participating are restricted to a window around the crop rows (82, 69). Single line Hough transform has also been used per independent frame (83), or in combination with recursive filtering of successive frames (84). In an effort to increase robustness, a pattern (multiple-line) Hough transform was introduced (85) that utilizes data from the entire image and computes all lines at once.

Researchers have also used stereo vision for navigation. In (86) an elevation map was generated and the maximum value of the cross-correlation of its profile with a cosine function (that represented crop rows) was used to identify the target navigation point for the vehicle.

In (87) depth from stereo was used to project image optical flow to vehicle motion in ground coordinates and calculate offset and heading using visual optical flow.

2.5.3 Limitations and possible directions

Most reported work was based on monocular cameras, with limited use of stereo vision and 2D/3D lidars. One reason is that in early growth stages the crops can be small in surface and short in height; hence, height information is not always reliable. Given the increasing availability of real-time, low-cost 3D cameras, extensions of some of the above methods to combine visual and range data are conceivable (e.g., visual and spatial texture; visual and shape features) and could improve robustness and performance in some situations. Also, given the diversity of crops, cropping systems and environments, it is possible that crop or application targeted algorithms can be tuned to perform better than 'generic' ones and selection of appropriate algorithm is done based on user input about the current operation. The generation of publicly available datasets with accompanying ground truth for crop lines would also help evaluate and compare approaches.

2.6 Tree-relative guidance in orchards

Orchards rows are made of trees, vines or shrubs. If these plants are short and the auto-guided robot is tall enough to straddle them, the view of the sensing system will include several rows and the guidance problem will be very similar to crop-row relative guidance. When the plants are tall or the robot is small and cannot straddle the row, the view of the sensing system is limited to two tree rows (left and right) when the robot travels inside an alley, or one row (left or right) if it is traveling along an edge of the orchard. Multiple rows may be visible only when the robot is at a headland during an entrance or exit maneuver. In this situation the images (and range data) captured by the sensing system look very different than between tree rows, and therefore the row-following sensing and guidance techniques cannot be used.

2.6.1 Agricultural domain background

The main approach is to detect the tree rows and compute geometrical lines in the robot's coordinate frame and use them for guidance. Robustness and accuracy are very important, because erroneous line calculations could cause the robot to drive into trees and cause damage to itself and the trees and orchard infrastructure. Although the problem seems well defined and structured, the following conditions present significant challenges: the presence of cover crops or weeds on the ground can make it difficult to discriminate based only on color; tall vegetation can hide tree trunks that are often used as target for row-detection systems; trunks from neighboring rows are often visible too; variability in illumination conditions during the day or nighttime operations (light intensity, gradients, shadows), and environmental conditions (e.g., dust, fog) affect sensing. Trees grow at different rates and may be pruned/hedged manually resulting in non-uniform tree row geometries. Also, there is a large variety in tree shapes, sizes and training systems, and orchard layouts, which makes it difficult to design ‘universal’ guidance algorithms that rely on specific features. For example, Figure 4a shows a recently established orchard with small trees right out from a nursery, where canopies are small and sparse; Figure 4b shows younger trellised pear trees; Figure 4c shows high density fruit-wall type trellised apple trees; Figure 4d shows old open-vase pear trees in winter; Figure 4e shows large, open-vase cling-peach trees; Figure 4f shows a row of table grape vines.

Figure 4 Examples of orchard rows: a) Recently established orchard with small trees right out from a nursery; b) Young trellised pear trees; c) High density fruit-wall type trellised apple trees; d) Old open-vase pear trees in the winter; e) Large, open vase cling peach trees; f) table grape vines with canopies covering the sky.

2.6.2 Existing approaches

Monocular vision has been used for guidance in orchards (88). In a *tree trunk-based approach* (89) visual point features from tree trunks are tracked and a RANSAC algorithm selects a number of inlier points whose locations are reconstructed in 3D using wheel odometry and the vehicle kinematic model. Then, lines are fitted to the points and an Extended Kalman filter integrates the vanishing point (row end) with these lines to improve their estimate. In (90) a *sky-based approach* is pursued, where the high contrast between tree canopies and the sky was used to extract the boundary of the portion of the sky visible from the camera, and from that the vehicle heading. In (91) the image is segmented into classes such as *terrain, trees and sky*. Then, Hough transform is applied to extract the features required to define the desired central path for the robot.

The fact that even young trees in commercial orchards extend much higher than the ground level (in contrast to row crops) has resulted in heavier use of ranging sensors for orchard guidance than what has been reported for row-crop guidance. In (92) a *2D laser scanner* was placed 70 cm above the ground, horizontally, and Hough transform was used to fit lines through the points sensed from trunks at the left and right of the robot. Line regression has also been used to fit lines (93) and was combined with filtering to improve the robustness of line parameter estimation (94, 95). Line-based SLAM (Simultaneous Localization and Mapping) was also proposed to simultaneously estimate rows and localize the robot with respect to them (96).

3D lidar has also been used to get range measurements from the surroundings (ground, trunks, canopies), given that 2D lidars can only scan at a certain height above the ground where tall vegetation or vigorous canopy growth may partially occlude or even hide trunks. In (97) the point cloud of each lidar scan is registered with odometry and combined with recent previous ones in a single frame of reference. Then, the left and right line equations for tree rows are computed in a RANSAC algorithm operating on the entire point cloud, and an Extended Kalman filter is used to improve the robustness of line parameter estimation. The lateral offsets of the fitted lines are refined further by using points from heights that correspond to trunks. Off the shelf, low-cost 3D cameras were used also to detect orchard floor and tree trunks (98). Random sampling and RANSAC were used to reduce the number of points and exclude outliers in the point cloud, and a plane was fitted to the data to extract the ground, whereas trees were detected by their shadows in the generated point cloud.

Sensor fusion has also been reported for auto-guidance in orchards. In (99) an autonomous multi-tractor system was presented that was used extensively in commercial citrus orchards for mowing and spraying operations. A precise orchard map was available depicting tree rows (not individual trees), fixed obstacles, roads and canals. An RTK GPS was the primarily guidance sensor for each autonomous tractor. However, tree growth inside orchard rows (e.g., branches extending in the row) often necessitates that the robot deviate from pre-planned paths. A 3D lidar and high dynamic range color cameras were used to build a 3D occupancy grid, and a classifier differentiated between voxels with weeds (on ground) and trees, thus keeping only voxels representing empty space and tree canopies. The row guidance algorithm used GPS to move towards the waypoint at the end of the row and the 3D grid to find the lateral offset that must be added to the original planned path to keep the tractor from running into trees on either side.

Robust, accurate and repeatable turning at the end of a row using relative positioning information with respect to the trees is very difficult (100) and has not been addressed adequately. A successful turn involves detecting the approach and the end of the current row, initiating and executing the turning maneuver, and detecting the entrance of the target row to terminate the turn and enter the next row. One approach is to introduce easily distinguishable *artificial landmarks* at the ends of tree rows (95, 60). Landmarks can be used to create a map (100), detect the end of the current row, the entrance of the next row, and localize the robot during turning, using dead reckoning. In (101) end-of-row detection utilized a 2D lidar, a camera and a tree-detection algorithm. Turning maneuvers were executed using *dead reckoning* based on wheel odometry. Dead reckoning with slip compensation has also been used (102).

2.6.3 Limitations and possible directions

Tree row detection and following has received a lot of attention in the literature. However, the lack of publicly available code and benchmark datasets have prevented the evaluation and comparison of existing approaches with respect to accuracy and robustness. 2D or 3D datasets with accompanying ground truth for vehicle pose with respect to the centerline would be invaluable for accelerating research, in analogy to computer vision (103). Also, sensor-based detection of row exit and entrance, and localization during turning between rows using relative positioning information with respect to the trees have not been addressed adequately.

3 Sensing the crop and its environment

In the context of agricultural robotics, sensing for crop production refers to the automated estimation of biophysical and biochemical properties of crops and their biotic and abiotic environment that can be used for breeding or crop management.

3.1 Agricultural domain background

Crop status and growth are governed by the interaction of plant genetics with the biotic and abiotic environment of the crop, which are shaped by uncontrolled environmental factors and agricultural management practices. The biotic environment consists of living organisms that affect the plant, such as neighboring plants of the same crop or antagonistic plants (weeds), bacteria, fungi, viruses, insect and animal pests, etc. The abiotic environment includes all non-living entities affecting the plant, i.e., surrounding air, soil, water (all sources) and energy (intercepted radiation, wind). The environment can cause biotic or abiotic crop physiological *stresses*, i.e., alterations in plant physiology that have negative impact on plant health and consequently yield, or quality. Examples include plant stress due to fungal diseases, water stress due to deficit irrigation, reduced yields due to weeds or drought, crop damage due to excessive temperatures, intense sunlight, etc.

The environment and potential stressors affect strongly crop physiological processes and status, which are expressed through the plant's *biochemical and biophysical properties*, some of which can be measured directly or indirectly. Examples of such *biochemical* properties are the number and types of volatile organic compounds emitted from leaves (104). Examples of biophysical properties include *leaf properties* such as chlorophyll content, relative water content and water potential, stomatal conductance, nitrogen content, as well as *canopy structure* properties. Canopy structure is defined as "the organization in space and time, including the position, extent, quantity, type and connectivity, of the aboveground components of vegetation" (105). Components can be vegetative (non-reproductive) such as leaves, stems and branches, or reproductive, i.e., flowers and fruits. Canopy structure properties can be based on individual components (e.g., number, size, shape of branches, flowers or fruits), on indices that characterize ensembles of components (e.g. fruit density per tree height zone) or indices that characterize entire plants, such as a canopy's leaf area index

(LAI). Finally, a special property, that of plant 'species' is of particular importance because it is used to distinguish crops from weeds and classify weed species for appropriate treatment.

Estimation of crop and environmental biophysical and biochemical properties is based on measurements that can be made through *contact or remote sensing*. Contact measurements are mostly associated with the assessment of soil physical and chemical properties and involve soil penetration and measurement of quantities like electrical conductivity or resistance (106). Contact sensing for crops has been very limited so far (107), partly due to plant tissue sensitivity and the difficulties of robotic manipulation (108). The large majority of robotic sensing applications involve *proximal remote sensing*, i.e., non-contact measurements - from distances that range from millimeters to a few tens of meters away from the target - of *electromagnetic energy* reflected, transmitted or emitted from plant or soil material; *sonic (mechanical) energy* reflected from plants; or *chemical composition* of volatile molecules in gases emitted from plants. Proximal remote sensing can be performed from unmanned ground vehicles (UGVs) or low-altitude flying unmanned aerial vehicles (UAVs) (109); sensor networks can also be used (110).

3.2 Existing approaches

Current technology offers a plethora of sensors and methods that can be used to assess crop and environmental biophysical and biochemical properties, at increasing spatial and temporal resolutions. Imaging sensors that cover the visible, near-infrared (NIR), and shortwave infrared spectral regions are very common. A comprehensive review of non-proximal and proximal electromagnetic remote sensing for precision agriculture was given in (111). Proximal remote sensing technologies for crop production are reviewed in (112); plant disease sensing is reviewed in detail in (113, 114); weed sensing is covered in (115), and pest/invertebrates sensing in (116).

One type of sensing involves acquiring an image (or stack of images at different spectra) of the crop(s), removing background and non-crop pixels (117), and estimating the per-pixel biophysical variables of interest, or performing species classification for weeding applications. Estimation is commonly done through various types of *regression* (parametric, non-parametric/machine learning) (118, 119). For example, during a training phase, images of leaf samples from differently irrigated plants would be recorded, and appropriate spectral features or indices would be regressed against the known (measured) leaf water contents. The trained model would be evaluated and later used to estimate leaf water content from spectral images of the same crop. Pixel-level plant species classification is done by extracting spectral features or appropriate spectral indices and training classifiers (115).

In other cases, estimation of some properties – in particular those related to shape - is possible directly from images at appropriate spectra, using established image processing and computer vision techniques, or from 3D point clouds acquired by laser scanners or 3D cameras. Examples of such properties include the number of fruits in parts of a tree canopy (120), tree traits related to trunk and branch geometries and structure (121, 122), phenotyping (123), shape-based weed detection and classification (115), and plant disease symptom identification from leaf and stem images in the visible range (124).

Crop sensing is essential for plant phenotyping during breeding, and for precision farming applications in crop production. Next, the main challenges that are common to crop sensing tasks in different applications are presented, and potential contributions of robotic technologies are discussed.

3.3 Challenges and possible directions

A major challenge is to estimate crop and environment properties – including plant detection and species classification – with *accuracy and precision* that are adequate for confident crop management actions. Wide *variations in environmental conditions* affect the quality of measurements taken in the field. For example, leaf spectral reflectance is affected by ambient light and relative angle of measurement. Additionally, the *biological variability of plant responses* to the environment can result in the same cause producing a wide range of measured responses on different plants. This makes it difficult to estimate consistently and reliably crop and biotic environment properties from sensor data. The responses are also often nonlinear and may change with time/plant growth stage. Finally, multiple causes/stresses can contribute toward a certain response (e.g., combined drought and heat) (125), making it impossible for an 'inverse' model to map sensor data to a single stress source.

Agricultural robots offer the possibility of automated data collection with a suite of complementary sensing modalities, concurrently, from large numbers of plants, at many different locations, under widely ranging environmental conditions. Large amounts of such data can enhance our ability to calibrate regression models or train classification algorithms, in particular deep learning networks, which are increasingly being used in the agricultural domain and require large training data sets (126). Examples of this capability is the use of deep networks for flower (127) and fruit detection (128, 129, 130) in tree canopies, and the "See and Spray" system that uses deep learning to identify and kill weeds (131). Data from robots from different growers could be shared and aggregated too, although issues of data ownership and transmission over limited bandwidth need to be resolved. The creation of large, open-access benchmark data sets can accelerate progress in this area. Furthermore, sensors on robots can be calibrated regularly, something which is important for high-quality, reliable data. Other ways to reduce uncertainty is for robots to use complementary sensors to measure the same crop property of interest, and fuse measurements (132), or to measure from different viewpoints. For example, theoretical work (133) shows that if a fruit can be detected in n independent images, the uncertainty in its position in the canopy decreases with n. Multiple sensing modalities can also help disambiguate between alternative interpretations of the data or discover multiple causes for them. New sensor technologies, such as Multispectral terrestrial laser scanning (MS-TLS) which measures target geometry and reflectance simultaneously at several wavelengths (134) can also be utilized in the future by robots to assess crop health and structure simultaneously.

Another major challenge is to sense all plant parts necessary for the application at hand, given limitations in *crop visibility*. Complicated plant structures with *mutually visually occluding parts* make it difficult to acquire enough data to reliably and accurately assess crop properties (123), recover 3D canopy structure for plant phenotyping or detect and count flowers and fruits for yield prediction and harvesting, respectively. This is compounded by our desire/need for high-throughput sensing which restricts the amount of time available to 'scan' plants with sensors moving to multiple viewpoints. Robot teams can be used to distribute the sensing load and provide multiple independent views of the crops. For example, fruit visibility for citrus trees has been reported to lie in the range between 40% and 70% depending on the tree and viewpoint (135), but rose to 91% when combining visible fruit from multiple-perspective images (136). A complementary approach is to utilize biology (breeding) and horticultural practices such as tree training or leaf thinning, to simplify canopy structures and improve visibility. For example, when V-trellised apple trees were meticulously pruned and thinned (manually) to eliminate any occlusions for the remaining fruits, 100% visibility was achieved (137) for a total of 193 apples in 54 images, and 78% at the tree bottom with an average of 92% was reported in (138).

Another practical challenge relates to the *large volume of data* generated by sensors, and especially high-resolution (multi-spectral) imaging sensors. Fast and cheap storage of these data onboard their robotic carriers is challenging, as is wireless data transmission, when it is required. Application-specific data reduction can help ease this problem. The necessary *compute power* to process the data can also be very significant, especially if real-time sensor-based operation is desired. It is often possible to collect field data in a first step, process the data off-line to create maps of the properties of interest (e.g., chlorophyll content maps), and apply appropriate inputs (chemicals, fertilizer) in a second step. However, inaccuracies in vehicle positioning during steps one and two, combined with increased fuel and other operation costs and limited operational time windows (e.g., due to weather) often necessitate an "on-the-go" approach, where the robot measures crop properties and takes appropriate action on-line, in a single step. Examples include variable rate precision spraying, selective weeding, and fertilizer spreading. Again, teams of robots could be used to implement on-the-go applications, where slower moving speeds are compensated by team size and operation over extended time windows.

4 Physical interaction with crops and growing environment

In the context of agricultural robotics, robots interact physically with crops and their growing environment by transporting mass, or by delivering mass or energy in a targeted/selective and controlled fashion. A major requirement is to *combine high throughput* (i.e., operations per second) with *very high efficiency*, i.e., percentage of successful operations).

4.1 Agricultural domain background

Interaction via mass delivery is performed primarily through deposition of chemical sprays (139) and precision application of liquid (140) or solid nutrients (141). Delivered energy can be radiative (e.g., laser) or mechanical, through actions such as impacting, shearing, cutting, pushing/pulling. In some cases the delivered energy results in removal of mass (entire plant or parts of it). Example applications include mechanical destruction of weeds, tree pruning, cane tying, flower/leaf/fruit removal for thinning or sampling, fruit and vegetable picking. Some applications involve delivery of both material and energy. Examples include blowing air to remove flowers for thinning, or bugs for pest management (e.g., strawberry *Lygus hesperus*); killing weeds with steam or sand blown in air streams or flame (115); and robotic pollination, where a soft brush is used to apply pollen on flowers (142).

Physical interaction with the crop environment includes tillage (143) and soil sampling operations (106), and for some horticultural crops it may include using robotic actuation to carry plant or crop containers (e.g., pots in nurseries or harvested trays of fruit), manipulate canopy support structures (trellis wires, posts) (144) or irrigation infrastructure (emitters, valves, lines) (35).

In general, applications that require physical contact/manipulation with sensitive plant components and tissue that must not be damaged have not advanced as much as applications that rely on mass or energy delivery without contact. The main reasons are that robotic manipulation which is already hard in other domains (108) can be even harder in agricultural applications, because it must be performed fast (for high throughput and cost-effective operation) and carefully, because living tissues can be easily damaged.

Manipulation for fruit picking have received a lot of attention because of the economic importance of the operation (145). Fruits can be picked by cutting their stems with a cutting device; pulling; rotation/twisting; or combined pulling and twisting. Clearly, the more complicated the detachment motion (and its control) is, the more time-consuming it will be, but in many cases a higher picking efficiency can be achieved because of fruit damage reduction during detachment. Fruit damage from bruises, scratches, cuts, or punctures results in decreased quality and shelf life. Thus, fruit harvesting manipulators must avoid excessive forces or pressure, inappropriate stem separation or accidental contact with other objects (146).

4.2 Existing approaches

Contact-based crop manipulation systems typically involve one or more robot arms, each equipped with an end-effector. Fruit harvesting is the biggest application domain (145), although manipulation systems have been used for operations such as de-leafing (147), taking leaf samples (148), stomping weeds (149), and measuring stalk strength (107). Arms are often custom designed and fabricated to match the task; commercial, off-the-shelf robot arms are also used, especially when emphasis is given on prototyping. Various arm types have been used, including cartesian, SCARA, articulated, cylindrical, spherical and parallel/delta designs.

Most reported applications use open-loop control to bring the end-effector to its target (137). That is, the position of the target is estimated in the robot frame using sensors and the actuator/arm moves to that position using position control. Closed-loop visual servoing has also been used to guide a weeding robot's (149) or fruit-picking robot's (150, 151) end-effector.

End-effectors for fruit picking have received a lot of attention and all the main fruit detachment mechanisms (pulling via grasp closure, suction or a combination of both) have been tried (152). Mechanical design and compliance have also been used to reduce the effects of variability and uncertainty. For example, properly-sized vacuum grippers can pick/suck fruits of various sizes without having to center exactly the end-effector in front of the targeted fruit (152, 153). Also, a large variety of grippers for soft, irregular objects like fruits and vegetables have been developed using approaches that include from air (pressure, vacuum), contact and rheological change (154).

Once a fruit is picked, it must be transported to a bin. Two main approaches have been developed for fruit conveyance. One is applicable only to suction grippers and spherical fruits, and uses a vacuum tube connected to the end-effector to transport the picked fruit to the bin (138). In this case there is no delay because of conveyance, as the arm can move to the next fruit without waiting. However, the vacuum tube system must be carefully designed so that fruits don't get bruised during transport. The other approach is to move the grasped fruit to some "home" location where it can be released to a conveyance system (e.g., a conveyor belt or tube) (137) or directly to the bin. This increases transport time, which may hurt throughput. Clearly, there are several design and engineering challenges involved with this step.

4.3 Challenges and possible directions

Combining high throughput with *very high efficiency* is a major challenge for physical interaction with crops in a selective, targeted manner; examples of such selective interactions are killing weeds or picking fruits or vegetables. For example, reported fruit picking efficiency (the ratio of fruits successfully picked to the total number of harvestable fruits) in literature for single-arm robots harvesting apple or citrus trees ranges between 50% to 84%; pick cycle time (average number of seconds between successive picks) ranges from 3 to 14.3s (145). However, one worker on an orchard platform can easily maintain a picking speed of approximately 1 apple per 1.5 seconds with efficiency greater than 95% . Hence, replacing ten pickers with one machine would require building a 10-40 faster robotic harvester that picks gently enough to harvest 95% of the fruit successfully, without damage, and do so at a reasonable cost!

Several factors render this combination challenging to achieve. Living tissues can be easily damaged and handling them typically requires slow, careful manipulation that avoids excessive forces or pressures. Biological variation introduces large *variability in physical properties* such as shape*,* size*,* mass, firmness of the targeted plants or plant components. This variability, coupled with uncertainty in the sensing system and limitations in the performance of control systems can affect negatively the accuracy, speed, success rate and effectiveness of the operation. Reduced accuracy can cause damage to the targeted part of the plant (e.g., a fruit being picked) or nearby plant parts (e.g., fruits, branches), or the entire plant (e.g., spraying part of the crop when targeting a nearby weed). It may also cause reduced throughput due to misses and repeats, or reduced efficiency (more incomplete operations) if no repeats are attempted.

Visual servoing/guidance of robot actuators can reduce uncertainty and increase efficiency, but uneven illumination, shadows cast by branches and leaves, partial occlusions, and branches acting as obstacles present significant challenges in real-world conditions (150). Guiding the end-effector by combining inputs from multiple cameras is an approach that could be adapted to agricultural settings (155). Another possible direction is using deep reinforcement learning to learn visual servoing that is robust to visual variation, changes in viewing angle and appearance, and occlusions (156).

Innovative end-effector design and control can also increase throughput and efficiency. If stem-cutting is used, challenges include detecting and cutting quickly and robustly from a large range of approaches, in the presence of touching (clustered) fruits and twigs. If pulling is used, the force required to detach fruits depends on the type and maturity of the fruits, the approach angle of the end-effector, and on whether rotation is also used. Some fruits require concurrent, controlled, synchronized rotation and pulling to reduce skin/peel damage at the stem-fruit interface (152), a task that is complex and not easily modeled. Deep reinforcement learning for grasping (157) is a possible approach to build sophisticated controllers for such tasks. Innovations in materials, design and control for soft robots could also be adapted to fruit picking and crop handling in general (158).

Another important factor is limited *accessibility* of the targeted plants or their parts by robot end-effectors. Accessibility can be limited by plant structure, positioning, interference with neighboring plants or structures, and robot design. For example, in robotic weeding, weeds that are very close to a crop-plant's stem and hidden under its canopy are not easily (or at all) accessible by the end-effector (spray nozzle/laser/hoe) without damaging the crop (159). In fruit harvesting, fruits in tree canopies that are positioned behind other fruits, branches or trellis wires also have limited accessibility by robotic harvesting arms. Accessibility can be improved by introducing dexterous, multi-dof actuation systems. However, control complexity (e.g., maneuvering, online obstacle avoidance) can reduce throughput; the overall system cost will also be higher. Breeding and horticultural practices can also be utilized to improve accessibility. For example, tree cultivars with smaller and simpler canopies, training systems that impose simpler - planar - canopy geometrical structures along fruit thinning operations can contribute to higher fruit accessibility/reachability. To some extent, it is the availability of trellised planar architectures and precision fruit thinning which result in very high fruit visibility and reachability that have enabled robotic harvesting to emerge recently as a potentially cost-effective approach to mechanical fruit harvesting at commercial scale. However, the cost and required labor demand for maintaining meticulously thinned and pruned trellised trees can be very high. Moreover, not all fruit trees can be trained in such narrow, planar systems.

A promising approach that can be used to guide "breeding for manipulation" is the use of plant and robot geometric models to co-design tree structures and machines to optimize manipulation reachability and throughput (160). Also, the use of large numbers of simpler, cheaper actuators (161) that approach plants from different positions has shown promise in terms of reachability (162), and could be adopted to increase overall throughput.

6 Summary and Conclusions

Agricultural robotics enable sensing and interacting with crops at fine spatial scales, even at the level of individual plants or plant parts. Thus, they enable high-throughput phenotyping for breeding improved crop cultivars, and ultra-precise farming, which is a key technology for increasing crop production in a sustainable manner. They can also generate crop-related data that can be used to increase food safety and traceability, and to optimize crop management. Furthermore, agricultural robots can reduce our dependence on unskilled farm labor, which is diminishing in many countries. Also, the emerging paradigm of replacing (for some operations) large conventional agricultural machines with teams of smaller autonomous vehicles could open up possibilities for dramatically changing the way we cultivate crops. Small machines reduce drastically soil compaction and are not necessarily restricted to crop rows; hence, they could be used to establish alternative, productive crop patterns that incorporate mixed-cropping, which is known to reduce pest pressures and increase biodiversity.

To accomplish their tasks, agricultural robotics face significant challenges. Their mechanical embodiments, electronics, and their sensing, perception and control software must operate with accuracy, repeatability, reliability and robustness under wide variations in environmental conditions; diversity in cropping systems; variation in crop physical and chemical characteristics and responses to environment and management, due to intraspecies biological variation; diversity and complexity of plant canopy structures. Essentially, agricultural robotics must combine the advanced perception and manipulation capabilities of robotic systems, with the throughput, efficiency and reliability of hard automation systems, in a cost-effective manner.

Disclaimer of endorsement

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