Smart automation in the agri-food chain: State of the art, prospects and impacts on workforce demands

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Abstract
Smart automation technologies are penetrating the agri-food sector at accelerating pace. Mobile robots and mechatronic systems offer advanced precision sensing and actuation capabilities for crop and livestock production. Robots that can handle soft, flexible objects are establishing their presence in the food processing sector. This paper presents a review of the underlying smart automation technologies that are expected to impact the largest segments of the farm workforce: equipment operators and workers who provide manual labor. It also highlights the main challenges for further advancement of these technologies and discusses emerging approaches to overcome them. Next, the paper discusses the effects of the two types of smart automation on the workforce in terms of changes in work demand and required skills. Finally, the development and adoption of smart automation is discussed and recommendations to enable smart farming technologies to reach mainstream farming are presented based on results from a European Union funded project. The paper focuses on the primary crop production part of the agri-food chain. However, the analysis of the requirements, challenges and current trends in sensing and actuation technologies for physically interacting with crops in the field is applicable to a large extent to the manipulation/handling of produce in the post-harvest chain.

1. Introduction
The agri-food chain encompasses breeding, primary production on the farm - including harvesting - post-harvest processing on the farm and beyond, and storage and distribution. The operations involved in agricultural primary production have been categorized as power-intensive and control-intensive (Binswanger, 1986). The former are performed uniformly and require high power intensity (e.g., tillage, threshing, crop transport). The latter are selective and require “judgment” (e.g., fruit harvesting, tree pruning). The term
Mechanization has been traditionally used to refer to the introduction and operation of machines by humans to interact physically with the crops, animals, and their environments, in the context of performing agri-food production operations. Mechanization revolutionized agriculture by increasing the efficiency of primarily power-intensive operations, thus replacing human labor in those operations. For example, as a result of mechanization, in the USA the average labor per acre to produce corn for grain dropped from 34.2 hrs in 1915-19 to 3.7 hrs in 1974-78 (Binswanger, 1986), to 2.7 hrs in 2015-17 (FINBIN, 2019).

The dichotomy between power and control intensive applications was bridged - to some extent - during the past 25 years by Precision Agriculture (PA) or Variable Rate (VAR) technologies. The introduction of increasingly powerful and low-cost computing platforms, sensors, electronics, actuators and software, along with the gradual deployment of the Global Navigation Satellite System (GNSS) resulted in ‘smarter’ mechanization that combines high throughput (power-intensive) operation with selective, variable and precise (control-intensive) applications of inputs (seeds, chemicals, water). PA technologies such as proximal and remote sensing and variable rate application do not affect labor demand (human labor hours per acre) significantly; instead, they improve the utilization of inputs for increased productivity and profitability and reduced environmental impact.

In recent years, advances in robotic/mechatronic technologies (computer vision, 3D sensing, and perception, machine learning, motion control software) have been incorporated into agricultural machines in two different ways. First, increased automated functions on existing machines (e.g., auto-steering, headland turning, implement control, real-time machine optimization). Second, smart robotic implements that attach to existing vehicles and perform highly selective operations (e.g., computer vision-based selective weeding), or self-propelled, autonomous robots of various forms and sizes (e.g., cabinless tractors, flying drones, multi-armed robots) that perform control-intensive tasks previously undertaken solely by people, such as scouting for disease or harvesting fruits. The same suite of technologies is disrupting the food processing sector of post-harvest handling, with robots undertaking tasks such as grading, sorting, cutting, processing, and packaging for products that until recently had been handled by humans. Finally, Internet connectivity makes it possible for data to be shared among machines at different stages of the agri-food chain,
thus creating opportunities for improved traceability, safety, and overall efficiency. The terms ‘smart automation’ or ‘smart farming’ are often used to refer to the collective use of hardware (computing and mechanical) and software to collect data, extract and process information from data, contribute to decision-making, and take physical actions to manage processes in the agri-food chain.

This paper presents a review of the underlying smart automation technologies that are expected to impact the largest segments of the farm workforce: equipment operators and workers who provide manual labor. It also highlights the main challenges for further advancement of these technologies and discusses emerging approaches to overcome them. Robotic weeding is presented as a case study of a technology that is already becoming commercial and will impact labor for organic farming. Robotic harvesting is also presented as an application that can disrupt demand for manual labor. Next, the paper discusses the effects of the two types of smart automation on the workforce in terms of changes in work demand and required skills. Finally, the development and adoption of smart automation is discussed and recommendations to enable smart farming technologies to reach mainstream farming are presented based on results from a European Union funded project. The paper focuses on the primary crop production part of the agri-food chain. Robotics and smart automation for food handling, processing and packaging is not addressed explicitly. However, the analysis of the requirements, challenges and current trends in sensing and actuation technologies for physically interacting with crops in the field is applicable to a large extent to the manipulation/handling of produce in the post-harvest chain.

2. Labor-impacting smart automation for crop production

Not all smart automation technologies are connected directly to significant potential changes in the demand for agricultural work. In 2017, in the USA, where agriculture is highly mechanized, the farm employment share of agricultural equipment operators was 18%. The share of farm workers in field crops, nurseries, greenhouses, farms, ranches, and aquaculture was 56% (a lot of manual farm labor is contracted and not included in this number); on-farm grading, sorting and packing was just 4%. In less mechanized countries farmworkers perform the tasks the machines could do, thus lowering the percentage of equipment operators. From the above, it seems that the automation technologies that
would have the most significant impact on farm labor are the ones that enable *full machine autonomy* (fewer operators required) or *targeted physical interaction with the crop and its environment* in ways that were not possible before (less manual labor required).

2.1 Fully autonomous operation of agricultural machines

Fully autonomous execution of a field operation requires: (a) autonomous navigation and (b) autonomous execution of all the tasks that must be performed during the operation. As it will be discussed next, the former is technically feasible, albeit with human supervision; however, the latter is complex, and supervised autonomy is the most likely operation mode for the near future.

2.1.1 Autonomous navigation

Autonomous navigation in field rows and headlands using GNSS is a commercially available technology for machines for field crops. The coordination and collaboration of more than one machines are also becoming commercially available. Autonomous navigation is not available yet for machines operating in orchards and vineyards. The main reasons are limited GNSS reliability due to foliage, lack of georeferenced maps that include static known objects/obstacles (e.g., trees, infrastructure), and dynamic environments where people, animals, or other vehicles may be present. Academic research groups (e.g., Radcliffe et al., 2018) and startup companies¹ are currently developing guidance technologies that use cameras and laser sensors - in addition to GNSS – to navigate inside orchard rows, and switch rows and orchard blocks. Mapping services are also becoming more affordable. Hence, at a technical level, accurate and reliable auto-guidance in orchards and vineyards should be available soon.

The issue of safety is very challenging, as technologies to detect and avoid collisions with unknown-unmapped obstacles like broken branches, people, animals, or other vehicles are not developed enough to provide safe driving with human-level performance.

2.1.2 Autonomous execution of agricultural operation-related tasks

Currently, auto-guided and automated agricultural machines have a human operator who provides the necessary awareness of the environment around the auto-guided vehicle for safe auto-guidance. In addition to safe driving, this operator is also needed to control and supervise the various tasks associated with the particular operation. For example, even on a highly automated combine, an operator is needed to watch the field for hidden obstacles and ditches, make sure that the header control is operating properly, watch for any debris that can clog the header or the chopper, make sure the grain is flowing smoothly into the grain hopper, and watch for unusual amounts of foreign matter in the grain. Fully autonomous execution of all tasks involved in agricultural operations requires advanced perception, situation awareness, judgment and task-specific knowledge. Such capabilities are not supported by current technology neither are they expected in the near future. However, remote supervised autonomy, i.e., remote supervision of one or several autonomous machines by an operator, shared autonomy and the ergonomics of such human-machine collaboration modes are established research areas (Goldberg, 2019; Wright et al., 2018) and remote supervision has been demonstrated recently for some agricultural applications executed by driverless machines (e.g., orchard spraying²). Of course, an appropriate legal framework must be developed before autonomous or remotely supervised machines are deployed; driverless agricultural machines are not legal in most countries.

2.2 Targeted physical interaction with crops and environment

In the context of smart automation, machines interact physically with crops and their growing environment by transporting mass, or by delivering mass or energy in a targeted (selective) and controlled fashion. The machine must be able to assess – using sensors and appropriate algorithms – the specific crop and environment properties that are necessary for targeted interaction. A major requirement is that automated targeted interaction combines high throughput (i.e., operations per second) with very high efficiency, i.e., percentage of successful operations) at reasonable cost. Closed-loop sensing and actuation is the major mode of operation during targeted interaction.

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² E.g., gussag.com.
2.2.1 Sensing

The assessment of crop and environment properties is possible from images at appropriate spectra, using image processing and computer vision techniques, or by processing 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 (e.g., for harvesting or thinning), tree traits related to trunk and branch geometries and structure (e.g., for pruning), shape (for weed detection and classification), and plant stress from leaf and stem images (e.g., for selective spraying or fertilizing). A primary goal is to estimate crop and environment properties – including plant detection and species classification – with enough accuracy and precision to support targeted actuation. 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 (Mulla, 2013; Gongal et al., 2015; Hamuda et al., 2016; Mahlein et al., 2018).

Crop and environment sensing technologies face significant challenges. 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, plant biological variability makes it difficult to estimate consistently and reliably crop and environment properties from sensor data. Another major challenge is limited crop visibility, which very often makes it hard to sense all plant parts necessary for the application at hand. Complicated plant structures with mutually visually occluding parts make it difficult to acquire enough data to reliably and accurately assess crop properties (Gibbs et al., 2017), recover 3D canopy structure or detect and count flowers and fruits for yield prediction and harvesting, respectively. This problem 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.

The most exciting development in sensing relates to machine learning, and in particular to deep neural networks, which are increasingly being used in the agricultural domain. These algorithms require large training data sets but can achieve significantly better results than conventional algorithms under various (and harsh) environmental and visibility conditions (Kamilaris and Prenafeta-Boldú, 2018). Examples of the use of this rapidly-evolving
technology include the use of deep networks for flower (Dias et al., 2018) and fruit detection (Sa et al., 2016) in tree canopies, and the “See & Spray” system that uses deep learning to identify and kill weeds (Ghostner, 2017). Breeding and horticultural practices (training, pruning, thinning) may also lead to simpler crop canopies and increased crop visibility but are associated with long time horizons and higher cost.

2.2.2 Actuation

Targeted physical interaction with crops and their environment is performed by transporting mass, or by delivering mass or energy. Mass delivery is performed primarily through deposition of chemical sprays and precision application of liquid or solid nutrients. Delivered energy can be radiative (e.g., laser weeding) or mechanical, through actions such as impacting, shearing, cutting. In some cases the delivered energy results in the removal of mass (entire plant or parts of it). Example applications include mechanical destruction of weeds, tree pruning, cane tying, flower/leaf/fruit thinning or sampling, fruit, and vegetable picking. Some applications involve the delivery of both material and energy. Examples include blowing air to remove flowers for thinning, or bugs for pest management and killing weeds with steam or flame.

The primary requirement and goal for actuation systems is that they enable operations at high efficiency and throughput. 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 considerable variability in physical properties such as shape, size, position, 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 the accuracy, speed, success rate and effectiveness of the actuation – and operation - negatively. Another factor is the limited accessibility of the targeted plants or their parts by machine end-effectors. Accessibility can be constrained by plant structure, positioning, interference with neighboring plants or structures, and robot design. Although accessibility can be improved if dexterous arms are used, such systems are expensive and require complicated controls, which can reduce throughput.
In general, applications that require targeted physical contact with or manipulation of sensitive plant components and tissue have not advanced as much as applications that rely on mass or energy delivery without contact. The main reason is that contact-based manipulation is a task with complex physics that cannot be modeled and controlled easily (Mason, 2018). Additionally, in agriculture it must be performed fast and carefully, as living tissues can be damaged easily. This explains to a large extent why most robotic applications involve non-contact operation (sensing, spraying) or destructive contact-based operation (e.g., mechanical weeding).

Several technologies are investigated to address the above challenges. Innovative end-effectors – including soft ones – that can handle soft, irregularly shaped and sized sensitive objects have been researched (Blanes et al., 2011) and introduced commercially (e.g., Soft Robotics, Inc.) Deep reinforcement learning for grasping (Quillen et al., 2018) is a possible approach to build sophisticated controllers for grasping and manipulation tasks. Accessibility can be improved significantly through breeding and horticultural practices. To some extent, it is the availability of apple tree cultivars that can be trellised and grow in “fruit wall” type planar architectures along with 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. Also, the use of large numbers of simpler, cheaper actuators that approach plants from different positions has shown promise in terms of reachability (Vougioukas et al., 2016), and could be adopted to increase overall throughput.

Next, two applications that are expected to have a significant impact on farm labor are discussed in greater detail. Robotic weeding is a technology that is closest to full commercial deployment, whereas robotic harvesting is a technology that can lead to the most significant reduction in demand for manual farm labor.

2.2.3 Automated weeding
Automated weeding robots promise to replace chemical herbicide application, allowing for sustainable and economically viable organic production systems without the need of enormous levels of hard labor. Automated intra-row cultivators make use of the known crop
row pattern (Pérez-Ruíz et al., 2012) or machine vision (Wang et al., 2019) to eliminate weeds without damaging the cultivated crops. Commercially available robotic weeders include the Ferrari Remoweed, Robovator, Garford In-row cultivator and Steketee IC (Perruzzi et al., 2017). These weeders detect crop row patterns (not weeds) and destroy weeds around the individual crop plants with cultivator knives. If weed populations are dense or tall enough to obscure the row pattern, then these machines do not function well (Fennimore and Cutulle, 2019). Computer vision and machine learning with deep networks is the current trend in weed recognition (Dyrmann et al., 2016). Large quantities of plant/seedling and weed image data are essential for training such algorithms and some researchers are working toward this (e.g., Olsen et al., 2019). BlueRiver Technology, purchased in 2017 by John Deere Co., is currently developing one of the first commercial vision-based robotic weeding systems called “See & Spray” (Chostner, 2017). This application is expected to grow fast, given the increasing number of herbicide-resistant weeds, the demand for organic produce and the huge labor demand of manual weeding.

2.2.4 Automated Harvesting
Selective robotic fruit and vegetable harvesting have received much attention from researchers and recently from start-up companies because of the economic importance of the crops and the amount of labor that harvesting them requires. For example, manual harvest costs in California make up 38% of total operating cost of apple production per acre (Klonsky & Stewart, 2014); for strawberries the percentage is 55.5% (Bolada et al., 2016). However, robotic harvesting is still at a pre-commercial stage, despite active research for at least 30 years (Bac et al., 2014). The machines developed so far have not achieved high enough efficiency and throughput to be cost-effective, mainly due to the sensing and actuation challenges presented in the ‘Sensing’ and ‘Actuation’ sections of this paper. Reported fruit picking efficiencies (FPE - percent of fruits successfully picked) in literature for single-arm robots harvesting apple or citrus trees range anywhere from 50% to 84%, and fruit pick cycle times (PCTs) range from 3 to 14.3s (Bac et al., 2014). These numbers are based on very limited (often unreported) numbers of experiments and picked fruits using conventional trees, i.e., non-trellised with large canopies. Recently, to overcome issues of poor fruit visibility (from occlusions from leaves, branches and other fruits) and reachability (from branches, fruits and wires), researchers developed robot harvesters for carefully
pruned and thinned V-trellised apple trees. Silwal et al. (2017) reported FPE=84% and PCT=6.0s for 150 apples with a $15k custom-made arm. A California-based startup company (Abundant Robotics, Inc.) reported FPE=91% for 372 apples on V-trellised trees that were thinned to single fruits inside the robot workspace and pruned to approximately 25 cm wide (Salisbury & Steere, 2017). Measured PCTs were not reported, although PCT in the order of 1 s was mentioned using a commercial ABB IRB 360 robot arm. Such a speed, if it can be sustained during the harvesting operation, is approximately 50% faster than that of one picker harvesting on an orchard platform.

Robotic harvesters typically involve one or more robot arms, each equipped with an end-effector. Arms are often custom designed and fabricated to match the task but commercial, off-the-shelf arms are also used, especially when emphasis is given on prototyping. End-effectors for fruit picking have utilized various fruit detachment mechanisms (pulling via grasp closure, suction or a combination of both). Mechanical design and compliance have also been used to reduce the effects of variability and uncertainty. For example, properly-sized vacuum grippers can pick fruits of various sizes without having to center exactly the end-effector in front of the targeted fruit. 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. 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) 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.

Currently, there are many start-up companies worldwide working on prototypes to harvest robotically strawberries, apples, kiwi fruits and broccoli and other crops in open fields, as well as sweet, bell and chili peppers, tomatoes, strawberries and cucumbers in greenhouses. Most of these machines are still slow and cannot pick all of the crop, mainly due to limited visibility and reachability. In the short-medium term, the ones that make it to the market will require that (fewer) human pickers are needed to harvest the crop that the robots cannot pick. In the medium to long term, advances in breeding, changes in crop
production systems and further improvements in sensing and actuation technologies can improve picking efficiencies and pick cycles, thus reducing further the need for unskilled manual labor.

4. Smart automation and workforce

Smart automation is changing the landscape of agricultural farm machinery in two ways. The first way relates to increased machine automation and autonomy. The large agricultural machines that mechanized power-intensive agricultural tasks during the twentieth century replaced anywhere from ten (tomato harvester - Thompson and Blank, 2000) to one hundred (cotton picker - Holley, 2003) unskilled workers with one skilled/trained machine operator. Advances in PA (variable rate) technologies, autonomous navigation and task automation on modern agricultural machines demand increased information technology skills and application-related knowledge and experience from the operator. (S)he needs to be educated in the use of the technologies and processes needed to configure, supervise, adjust and optimize the operating parameters of the equipment. Remote supervision of teams of autonomous machines may slightly reduce the required number of operators, but it will increase the demand for their technical and application-related expertise significantly.

The second way smart automation can change the mechanization landscape is through the introduction of robotic systems (smart implements or self-propelled) that interact with the crop and environment in targeted/smart ways that so far have been possible only for humans (control-intensive tasks). Examples include fruit and vegetable harvest-aids and robotic harvesters, and selective weeding via spraying or mechanical removal. For example, Schupp et al. (2011) reported labor savings ranging from 9.8% to 49.2% when an automated orchard platform was used for apple picking. A romaine lettuce harvester that uses waterjets to cut lettuce heads adaptively has reportedly cut by 50% the number of ground picking crews, which were between 24 and 30 people (Growing Produce, 2014). Mosqueda et al. (2017) tested four automated lettuce thinners that operated based on the selective spraying principle and reported that, on average, 2.03 person-hours and 7.31 person-hours per acre were needed to thin the lettuce plots with and without the machine, respectively (72% reduction in unskilled labor). Sørensen et al. (2005) estimated that steaming and robotic weeding platforms could reduce total farm labor (through reductions in hand
weeding) by 60–85% for farmers growing carrots and beets, respectively. Regardless of whether these robotic machines are owned by the grower or operate on a service business model, skilled operators will be required to configure, run and supervise them.

Overall, smart automation is expected to increase the demand for operators with advanced skills related to automation and information technology. Educational institutions at various levels should adjust their curricula to offer such skills. Shortage in the supply of such workers is not unlikely, as these skills could enable them to work for higher salaries in higher value industries. Robots that can manipulate the crop and its environment selectively can reduce the demand for manual labor significantly. Harvesting and automated weeding machines have been reported to reduce labor by 50% to 85%. Harvesting is perhaps the most challenging application to automate and the one that will result in the most significant reduction of labor in absolute terms.

5. Development and adoption of smart automation

Large agricultural equipment manufacturers are the leading developers of auto-guidance and task-automation technologies for farm machines. Smaller start-up companies lead innovation in robotic implements and agricultural robots that manipulate crops. An obstacle to the development of such robots is that each crop has its characteristics, and targeted manipulation of the crop often requires individual, custom-designed machines. Unless the crop has high value and volume to justify research in its mechanization, it will not happen. Furthermore, developing smart automation for a crop requires – in addition to capital - the capacity to conduct innovative R&D locally, as access to the crop is essential. For most countries in the developing world, these two conditions are not met. This may explain why some crops have substantial production volume (and overall value), but their mechanization has not advanced as expected. For example, the harvesting of cocoa pods and palm fruits (for oil) is performed manually; this is due to some extent to the technical difficulties involved in automating these tasks, but also to lack of local access to engineering expertise.

As a consequence, it may take a while until many local crops in Africa and Asia become mechanized. The second way smart automation can change the mechanization landscape is through the introduction of robots (smart implements or self-propelled) that interact with
the crop and environment in targeted/smart ways that so far have been possible only for humans (control-intensive tasks). Examples include fruit and vegetable harvesting, and selective weeding.

Despite the keen interest in smart farming, the adoption of smart automation and PA/VAR technologies is still slow (Schimmelpfennig, 2016; Barnes et al., 2019). High investment costs remain one of the most significant barriers, especially for small farms. There is a perception that the return on investment is uncertain. Farmers and advisors demand empirical based evidence about the economic benefits in yield performance and on more efficient use of inputs through in-field evidence and demonstration from impartial actors. The perception about the usefulness of smart farming technologies is almost exclusively based on economic performance, overlooking the environmental impact or the improvement of work conditions.

Based on information gathered from farmers a European Union funded project called Smart-AKIS (www.smart-akis.com) concluded in the following recommendations to enable smart farming technologies to reach mainstream farming:

(i) Develop decision support tools and services by advisors and agronomists to support investment decisions based upon performance, and accompany users in the setup and maximum use of purchased equipment.

(ii) Conduct independent and neutral research and demonstrate solutions to a large number of farmers and advisors covering a variety of soils and crops. Implement feedback mechanisms to collect and share information on the economic profitability of new technologies. Improve the marketing and communication efforts by industry, bridging the gap in terms of language, culture, and expectations with the farmer and advisor community. Promote independent organizations for conducting benchmarking studies of smart farming technologies, including cost/benefit analysis calculations.

(iii) Disseminate and demonstrate successful business cases as good practices at the farm level by testimonials from early adopters, peer-to-peer exchanges and demonstration.

(iv) Promote farm clusters or communities for data collection, allowing for trials and demos with field-scale and long-term experiments for benchmarking of data between
farms. Support demand-side policies with stricter environmental and food safety regulations, as smart farming technologies will ease regulatory compliance. Disseminate easy to understand and use databases, repositories, and resources, with audio-visual materials and practical information about smart farming uses and benefits.

Independently of the above findings, an important remark concerns the interplay between autonomy and machine size. The trend in self-propelled agricultural machinery so far has been to increase vehicle size for increased throughput. However, soil compaction and cost limit the perpetual continuation of this paradigm. Given that autonomous machines do not need space for an operator and that multiple machines can achieve high work efficiencies via coordinated and optimized operations, a possible future is smaller highly-automated agricultural machines. These may be easier to afford and safer to operate thus making it possible to deploy them in smaller farms.

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