Computational Contributions to the Automation of Agriculture

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Abstract

The purpose of this paper is to explore ways that computational advancements have enabled the complete automation of agriculture from start to finish. With a major need for agricultural advancements because of food and water shortages, some farmers have begun creating their own solutions to these problems. Primarily explored in this paper, however, are current research topics in the automation of agriculture. Digital agriculture is surveyed, focusing on ways that data collection can be beneficial. Additionally, self-driving technology is explored with emphasis on farming applications. Machine vision technology is also detailed, with specific application to weed management and harvesting of crops. Finally, the effects of automating agriculture are briefly considered, including labor, the environment, and direct effects on farmers.

Computational Contributions to the Automation of Agriculture

Robotic, and other computer-based advancements could prove to be vital for the future of agriculture. Currently, the rate of crop production is not rising at the same rate as population growth (Belton, 2016). According to the United Nations Food and Agriculture Organization, food production must be boosted by 70% or more in order to meet the needs of the growing population (Rejcek, 2017). This prediction of need has led to increasing interest in the field of agricultural development. Traditionally, research and development efforts have focused on increased crop breeding and genetic modifications for increased productivity (Ball et al., 2016). In more recent years, however, experts in robotic and computer fields have considered this problem as well. Agricultural robotics seems to be a promising field for producing more food at a sustainable rate and at a lower cost (Belton, 2016).

While robotic and computer technologies can be applied to virtually every aspect of agriculture, “systematic, repetitive, and time-dependent tasks seem to represent the best fields of application for robots” (Ampatzidis, De Bellis, & Luvisi, 2017, p. 1). These operations are often the most expensive without automation because of manual labor requirements and lend themselves to less expensive automation. For example, controlling weeds within a crop field is not only time consuming, but also relies on fallible human discernment of weeds. Similarly, the management of water for crops is a key part of the agricultural growth process and can be hard to do precisely without advanced technology. While underwatering can cause drying out of crops, overwatering can be just as damaging with respect to excess water and pathogens (Ampatzidis et al., 2017). These represent just a small sample of the many problems within the agricultural space that computer technologies are currently solving or are expected to solve in the future. Advancements such as machine vision, machine learning, image analysis, GPS, and wireless networking all contribute to the current and future success of agricultural technology. This paper will examine the various ways in which these and similar technologies affect agriculture, and ways to increase technological impact in the future.

Current Automation Solutions

Currently, there are few commercial robotic agriculture systems on the market. Most of the current work is research and experimentation, with some products reaching limited markets. This slow adoption of technology in agriculture has not stopped some farmers from adopting their own homemade solutions to agricultural issues. Many farmers have modified their farming machinery to perform various tasks remotely and, in some cases, automatically. One example is Kyler Laird, a farming “hacker” with a master’s degree in agriculture engineering (Bedford, 2017). By adding computer controllers to machinery, Laird employs machines performing autonomous drilling, planting, and harvesting of his crops. Being the owner of a small farm, Laird does not necessarily have the money to hire and pay continuous expenses for labor, but making smarter machinery is within his ability and resource constraints. Other farmers in conjunction with Purdue University started the agBot Challenge, a technology competition for various specific agricultural issues. Recently, the agBot Challenge featured a competition to make a robot capable of planting corn in a field. While in some cases these solutions may seem cobbled together and unprofessional, it is important to note that agricultural technology is not simply theoretical or stuck in experimental labs but is used daily by farmers around the world.

Ongoing Automation Research

Professional research and experimentation currently being completed on agricultural applications of technology typically can be considered in two separate categories. Digital agriculture refers to the use of data and computational techniques in order to make informed decisions about managing crops (Young, 2018). One example of this involves using weather patterns, soil conditions, and other factors to decide on the optimal crop for an area. The second field of agricultural technology is precision agriculture, which involves executing an agricultural plan precisely including specific steps in managing field tasks. This often requires specialized, technology-driven, equipment and the information gained from digital agriculture (Young, 2018). An excellent example of precision agriculture is the Hands Free Hectare project. This project involves the use of drones and automated machinery to grow an entire cereal crop without humans ever setting foot in the field (Belton, 2016). The precision of this technology allows for such a feat of agriculture, completely remote farming without direct human interaction, to be possible. Future advancements in both digital and precision agriculture, as well as developing relationships between the two are the keys to further advancing agriculture and solving the issues facing agriculture in general.

Digital Agriculture

Digital agriculture can take on many forms, but almost all digital agriculture-related systems involve a variation of data collection followed by computer processing to bring new information or services to farmers. Technologies such as drones, satellites, and wireless sensor networks are often used in the data collection phase of digital agriculture. Computer processing of this data can take many forms including simple visual portrayal of data, comparisons with norms for crops, and even advanced image processing. The benefit for a farmer from digital agriculture is additional analysis of their crops and information that may have previously been unavailable to him.

Services provided through agricultural data. As previously mentioned, the major benefit of digital agriculture is the provision of digital and internet-based services to assist farmers. Digital agriculture services often follow either a predictive approach or a reactive approach. A predictive approach will attempt to use historical data based on the farmer's specific situation to predict crop performance, whereas a reactive approach is based on real-time monitoring (Gebbers & Adamchuk, 2010). Both approaches allow farmers to track the health of crops, predict yields of their fields, and analyze the performance of different crop types through monitoring of weather, drone data, planting machinery data, and soil (Young, 2018). Yield prediction and other services can be especially beneficial when used by multiple farmers in a single area (Srininvasulu, Sarath, & Venkat, 2016). Having a larger data set for algorithms to operate on allows farmers more accurate predictions for their region. Yield maps sourced from multiple data types can help a farmer to understand the overall impact of both natural conditions and their own management activity (Gebbers & Adamchuk, 2010). With this information, farmers can make more informed decisions on fertilizers, crop types, and even estimate profits before a crop season begins.

Wireless sensor networks. One of the key needs in digital agriculture is having enough data for computational analysis and provision to services. According to Srbinovska, Gavrovski, Dimcev, Krkoleva, and Borozan (2015), "wireless sensor network (WSN) technologies are the major driver of the development of precision agriculture" (p. 297). Wireless sensor units are a relatively new technology that provide monitoring of specific parameters digitally for a minimal cost. The specific parameters monitored could include light, moisture, temperature, and any number of other values essential to the growth of a specific crop. Typically, sensor units are composed of a radio frequency transceiver, a microcontroller, a power source, and a specific sensor. Each small, low-range sensor unit transmits data to a more formidable wireless information unit, where data can be transferred to the internet or processed directly on the unit (Gutierrez, Villa-Medina, Nieto-Garibay, & Porta-Gandara, 2014). This form of networking provides widespread monitoring of crops, without the need to invest in hundreds of internet-enabled or long-range sensor units. While current applications of the technology are being used primarily in greenhouses, the technology has been tested on and could be adopted in outdoor situations.

Data collection by drones and satellites. In addition to WSN technology, drone technology has matured to the point where it is relatively inexpensive and reasonable to use for farm data collection. The most common method for drones to provide data through is imagery. An ideal future for many farmers would be the ability to mount a camera onto a drone and have it examine their fields every morning, reporting back on any issues discovered within the field. The drone would be able to pinpoint an unhealthy spot in a field and even potentially reveal the cause of issues (such as pests or irrigation issues). In many ways, this is already possible through RGB cameras (capturing visible red, green, and blue light), multispectral cameras, and computer analysis (King, 2017). Optical sensors that capture the visible and near-infrared spectra (Vis-NIR spectra) of a field can help to estimate a plant's biomass, chlorophyll content, and stress (Gebbers & Adamchuk, 2010). Invisible wavelengths of light, specifically ultraviolet or infrared, can be indicative of health characteristics in both crops and soil. Dead or unhealthy portions of crops will typically reflect more red light, while a healthy crop will absorb most red light and reflect near-infrared light. The Normalized Difference Vegetation Index, or NDVI, is an analysis of the photosynthetic activity of plants determined by examining the ratios of reflectance of red and near-infrared wavelengths (Corrigan, 2018). Following drone collection of imagery, computer software can be used to determine the NDVI and identify areas of crop fields. A high reflectance of visible light often results from the pigment in leaves for example, while water absorbs near-infrared wavelengths. Stagnant water with a high algae concentration will reflect more visible light in addition to absorbing near-infrared (Corrigan, 2018). With these specific characteristics built into software, farmers can view digital maps of their fields and identify potential problem spots where crops are dying or there are large accumulations of standing water. Satellites can be used in the same way and in past tests have been able to forecast the yield of a field with 99% accuracy based upon the current health and these other parameters (Rejcek, 2017). While satellite use in agriculture is mostly limited to data collection and analysis, drones have additional applications within precision agriculture.

Precision Agriculture

While digital agriculture is primarily focused on the collection of additional agricultural data and computer analysis, precision agriculture makes use of advanced technology and machinery to fully automate various processes within a farm. One of the biggest robotic advancements with application to agriculture is self-driving technology. Machinery that can move throughout fields autonomously is critical to the complete automation of farming tasks. Beyond navigation, methods for automating weed control (through both physical weeding as well as herbicide application) are extremely beneficial and even vital to the health of plants. Similarly, a method of watering crops autonomously and precisely is essential to the growth of a crop. Some research has also been done on fully automating the harvesting process, although harvesting can vary wildly between crop types. Automation research and experimentation has been completed in each of these areas, in anticipation of fully automating a farm.

Self-driving technology. Automating machinery movements through a field is in many ways the most critical portion of automating farming from plowing to harvest. Virtually every piece of equipment used on a farm requires precise movement through a field to accomplish its task without damaging the crop. There have been various approaches to accomplishing automation of navigation for machinery, but the most precise and revolutionary approaches have begun to utilize machine vision. Perfecting this technology will be critical to the success of complete automation attempts on farms.

Key considerations. When approaching the task of automated navigation within a farm there are several critical considerations. Machinery must be small, with the ability to hold cameras or any required sensors, but without damaging the surrounding environment and crops. In addition, a lightweight vehicle is essential to not damage the soil through excess compaction. Finally, obstacle avoidance is crucial. When a machine encounters an obstacle between rows of crops it must be able to avoid the obstacle without getting off track drastically and causing damage to surrounding crops (Kaivosoja, Jackenkroll, Linkolehto, Weis, & Gerhards, 2014). The primary goal is a reliable, precise, and small machine capable of driving itself between crop rows without damaging plant life and health.

Approaches to automation. With these considerations in mind, there are numerous approaches to automated or semi-automated navigation within fields. Older technology provided visual feedback for machinery to look for, using illuminated objects to assist in steering. This methodology was rather rudimentary and gave way to GPS (Global Positioning System) guidance, in which machinery moves based on satellite positional data (Gebbers & Adamchuk, 2010). These types of vehicles are classified as automated guided vehicles (AGVs), which incorporate a computer system and are capable of certain autonomous actions without outside input. Aside from GPS, AGVs can incorporate cameras, wheel odometry, and control scripting. Control scripting allows regions to be defined beforehand for a robot with the AGV deciding on motion actions needed to approach the regions (Kaivosoja et al., 2014). Each of these methods have varied success rates but utilizing multiple approaches together could be the future of agricultural navigation technology.

Machine vision assisted navigation. Machine vision has proven to be one of the key drivers in automated navigation technology. Ball et al. (2016) researched ways to incorporate machine vision with GPS and wheel odometry to navigate a test vehicle through a field and avoid obstacles along the way. Their test vehicle incorporated two forward facing cameras, quadrature encoders to measure speed and direction, an inertial measurement unit, a GPS module, 3G internet connectivity, a strobe light for nighttime running, and two computers. Through computations on the sensor inputs, researchers accomplished precise automation of the vehicle through a field, avoiding all obstacles and maintaining a navigation error less than 0.1 meter.

The primary computer focuses on direct navigational and vehicle control tasks. While GPS is a common technology for precise navigation, the outages in signal from satellites mean that expensive, precise sensors are needed (Ball et al., 2016). For the average farmer, this is not very practical, especially when multiple machines are likely needed. Instead, by fusing the inputs of multiple low-cost sensors, sensor outage catastrophes can be prevented, and the overall cost can be minimized. To enhance the precision of GPS sensors on vehicles, real-time kinematic (RTK) positioning data can be obtained from the 3G internet connection. RTK data allows GPS signals to be better adjusted to the exact sensor location. In the case of the unit in farming technology, this allows an accuracy of tens of centimeters to the exact location.

Beyond GPS technology, machine vision is used to track crop rows visually. Images taken from the two forward facing cameras are initially converted into grayscale and then down sampled to a lower quality to increase processing speed. Using data from the inertial measurement unit, a projection of the overhead view can then be generated, correcting for the tilt of the cameras mounted on the vehicle. The computer system then detects parallel textures, which are crucial to identifying rows within the image, as seen in Figure 1 (Ball et al., 2016). Additionally, by setting a tolerance for acceptable parallel texture strength, the machine can detect when it has reached a dead spot, the end of a row, or numerous other anomalies. With a proper map of the crop rows, the vehicle can follow the parallel textures to maintain a proper course through the field.

Before actual movement takes place, however, the various data inputs must be fused. With velocity being measured via sensors in the wheels and rotation of the vehicle determined by the visual tracking of crop rows, the error in GPS signal can be estimated. With this data and calculation, the vehicle's precise location can be determined, and the vehicle controller can set the throttle, steering angle, and brake as necessary (Ball et al., 2016). Reliance on a multitude of sensing technologies provides extreme reliability by allowing for outages in the sensors to be accommodated without disastrous effects. Difficulties do arise, however, when obstacles are present, resulting in the need for a more advanced obstacle detection system.

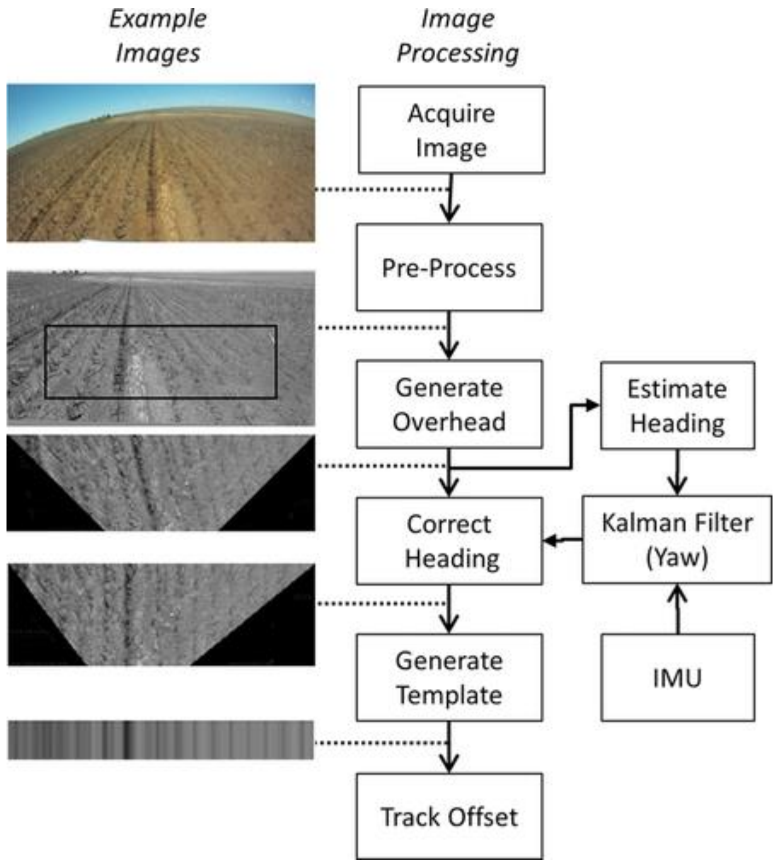

Figure 1. Image processing flow for crop row detection. Reprinted from "Vision-based Obstacle Detection and Navigation for an Agricultural Robot," by D. Ball, B. Upcroft, G. Wyeth, P. Corke, A. English, P. Ross, . . . A. Bate, 2016, *Journal of Field Robotics, 33*(8), 1115. Reprinted with permission.

Obstacle detection methods are still being explored, but current models focus on the assumption that certain crops produce distinct uniform environmental appearances (Ball et al., 2016). Through machine learning, a vehicle can adapt and learn the characteristics of the specific crop environment in which it is placed. Under this assumption, potential novel regions of the field can be detected by cameras. The use of multiple cameras allows for stereo matching of images, producing a 3D mapping of the potential obstacle. The algorithm for obstacle avoidance then expands this 3D mapping to account for error, flattens it into a 2D overhead view, and determines the closest route to return to the original path (Ball et al., 2016). The cameras continually search for obstacles, protecting from the possibility of multiple close together obstacles disrupting navigation or damaging machinery.

The end results of the test vehicle operating with machine vision assisted navigation and obstacle detection system are impressive. In a whole field test, 99.54% of the field was covered, with an 8.77% overlap or regions due to obstacles introduced in the test. All obstacles placed in the field were avoided, but in some cases, the algorithm expanded the boundary of the obstacle wider than needed. Finally, in simulated GPS outages for 300 seconds (with a travel distance of around 400 meters each time), the vehicle sustained navigation with a less than 0.1-meter error because of the visual crop row tracking (Ball et al., 2016). Such small margins of error represent a significant accomplishment and advancement beyond somewhat rudimentary GPS-based navigation. These results also present a promising future for automation and navigation and the ability to utilize this technology within a multitude of farming tasks.

Automated weeding and herbicide application. One of the key factors affecting crop growth failure is the presence of weeds. As a result, a critical point of agricultural automation for reliable crop growth is automating the process of weed removal. There are two main classifications of weeds within row crops, inter-row weeds and intra-row weeds. Inter-row weeds are unwanted plant growth in between rows of crops, which can be easily removed with standard machinery attached to a self-navigating tractor (Nan, Chunlong, Ziwen, Zenghong, & Zhe, 2015). Accordingly, very little additional research time has been devoted to further advanced automation methods on inter-row weeding. Intra-row weeds are weeds growing within crop rows, in between and around the individual crops (Nan et al., 2015). These weeds present a greater problem for farmers and require more care and attention for removal. In organic agriculture, intra-row weeds must be removed by hand, while conventional agriculture relies on herbicidal chemical treatments (Nan et al., 2015). Most automated weeding research is therefore dedicated to the problem of intra-row weeds. Automation advancements have been made for use in both conventional and organic crop farming, with methods to identify and remove weeds as well as precisely distribute herbicides.

Key considerations. In order to automate the weeding process, there are several key considerations to ensure proper weed removal without crop damage. Due to varying weed shapes and sizes, it is hard for machine vision to perform exact matching on weeds and crops (Ampatzidis et al., 2017). Machinery must have a built-in tolerance for this variation in order to prevent crop damage, while still maximizing the amount of weed removal. One additional consideration is the major role of light. When identifying crops and weeds, objects and key identifiers can be obscured or appear differently due to reflections (Ampatzidis et al., 2017). Machinery must be able to accommodate for light’s role, or farmers must implement strategies to minimize the impact.

Further considerations in the space are the actual requirements to implement a fully autonomous weeding system. Currently, there is a disconnect between the robotic and weeding elements implemented in so-called automated weeding system (Merfield, 2016). As previously mentioned, inter-row weeds are typically handled with standard weeding machinery attached to a self-navigating tractor. Researchers have taken a similar approach with handling of intra-row weeding, resulting in significant amounts of human setup and oversight of machinery for successful operation (Merfield, 2016). A true automated weeding system would not only perform weeding tasks but also handle these other difficult operations. A system should be able to monitor crop growth, soil conditions, and weed growth at all times in order to make a decision on when to weed. In the case of herbicidal methods, the weeding machine should also be able to choose a proper herbicide based upon the crop being grown (Merfield, 2016). Research in each of these fields will be crucial to the complete automation of the weeding process in agriculture.

Machine vision-based weed detection. One of the most significant advancements in weeding technology is the use of machine vision for weed detection and removal. By mounting a color camera and industrial control computer to a weeding platform with three rotating blades, researchers have been able to successfully accomplish automated weeding in this way (Nan et al., 2015). Crop and weed identification can be achieved through advanced image processing upon the resultant photographs from this machinery. Initially, an algorithm known as the excess green index is used to transform color images into monochrome, as displayed in Equation 1 (Nan et al., 2015). R, G, and B represent the intensities of the red, green, and blue color channels, with M being the resultant grayscale intensity for the pixel.

$$M = \begin{cases} 255 \times \min(g - r,\ g - b), (G \geq R \text{ and } G \geq B) \\ 0,\ \text{otherwise} \end{cases} \quad (1)$$

This algorithm creates a grayscale image designed to enhance vision of crops by converting stronger green shades into blacks while reducing soil color to white coloring. The result is extremely beneficial, for plant life detection, but does suffer from image noise as a result of soil color discrepancy and color distortion. In order to eliminate this noise, a pixel histogram is constructed based upon black pixel positioning. Smoothing the curves of the histogram and converting the pixels in significantly lower regions into white pixels effectively removes any remaining noise. Finally, based on this image, crop locations can be determined, and a safe region set around them to prevent crop and root damage (Nan et al., 2015). The attached rotating blades can revolve around this safe area under the soil, cutting the roots of any weeds in between crops.

This method of weed detection is detecting green plant life within the expected crop growth regions, and not directly identifying the weeds. Areas outside of the identified crop regions can then be weeded safely without damage to crops. While a more accurate method could be constructed by training a machine to identify weeds, such a method would be significantly more costly and computationally intensive. Accordingly, using a low-cost method (such as the one described) is preferred for most agricultural applications, provided it is accurate and reliable.

The results of using this method for weed detection and removal are quite astounding. Crop area detection had an error margin of ±15mm, primarily due to distortion of lenses and the variations in the setup of different crop rows. The recognition rates of crops, however, were all over 95% after testing on cauliflower, maize, and lettuce crops. One key influencer of this recognition rate was the use of a fixed area threshold, which could have missed underdeveloped plants and identified them as weeds (Nan et al., 2015). While delaying weeding to allow crop development could potentially solve this issue, timing would need to be precise to prevent weeds from leaching nutrients from crops. The use of the pixel histogram to reduce noise, while beneficial, could be aided by an adaptive threshold to prevent erroneous weed detection. Similarly, unhealthy plants were not always perfectly detected, since the excess green index struggles with discolored crops. Additionally, when large weeds were present near a crop they were sometimes masked into the safe area, resulting in weeds not being detected for removal (Nan et al., 2015). All these areas are important for further research to advance progress in automated weed technology. This system is already capable of an efficiency of 34.3 times that of a standard human laborer manually weeding, with the ability to cover 2.4 square hectometers of crop in an eight-hour work day as compared to a human's 0.07 square hectometers in the same time (Nan et al., 2015). Improving the accuracy of detection will enable the use of this technology in farms on a wider scale.

Automating herbicide application. Conventional agriculture relies on the distribution of herbicides for weed prevention and removal rather than manual removal of weeds by laborers. Precision agriculture aims to improve on this method by targeted herbicidal application, reducing quantities of herbicide needed, and reducing environmental impact. Blue River Technology, a John Deere company, has attempted to accomplish this through their "see-and-spray" technology in development. Using machine vision-based methods like the ones previously mentioned, machinery is able to spray weeds with herbicides, and additionally spray crops with fertilizer. This technology eliminates up to 90% of chemical use as compared to a standard herbicidal spraying method (Rejcek, 2017). While still struggling from some of the same accuracy concerns as previous machine vision examples, this is promising for herbicide application.

Researchers have also begun to test similar methods using drones. A camera mounted drone with enough computational power should be able to utilize the same algorithms for weed and crop identification. The locations of weeds can then be relayed to farmers through a graphical representation for removal. The true benefit of using drones, however, is the ability to mount herbicide sprayers to the drone itself for immediate application upon identification (King, 2017). Primary issues with this method are the cost and weight of equipment, which are interrelated. In order to accomplish computations required for weed identification, a reliable computing unit must be mounted on the drone along with the camera, herbicide reservoir, and spraying technology. Drones that are able to lift this amount of weight typically cost significantly more than a drone just being used for aerial imagery. One possibility to reduce costs would be using a centralized computing unit on the ground, with drones transmitting data, but the latency in transmission has not been studied extensively. Furthermore, studies have not been done on whether the cost savings of the reduced herbicide use would balance out drone cost, but this is an important area of consideration for future research. Overall, the future of automated weeding technology seems promising.

Automated crop irrigation. Beyond weed growth, a significant factor in plant health is water provision and intake. Studies reveal that around 85% of the available freshwater on earth is being used in agricultural applications (Gutierrez et al., 2014).

Strategies are certainly needed to optimize the use of these resources, especially considering growing food source needs. While primarily tested in greenhouse settings, wireless sensor networks are one way that water usage can be optimized without affecting crop growth. WSNs are composed of both wireless sensor units and wireless information units. Sensor units contain soil moisture and temperature sensors, combined with a ZigBEE radio connection. The ZigBEE protocol enables low power transmission of data with a reliable range. Wireless information units in the setup collect data from multiple sensors and determine whether to water crops. An attached pump allows the information unit to irrigate the crop through standard drip holes, controlling the water output and timing based upon sensor data. Additionally, a GPRS (General Packet Radio Service) module allows the information unit to broadcast data to a private internet portal where a farmer can perform real-time monitoring of the system. The farmer can also override the system to directly water fields if desired (Gutierrez et al., 2014). Using this method for automated irrigation is certainly promising for farmers looking to automate agricultural processes. As compared to a standard irrigation technique, WSN-based irrigation provides 90% savings of water with relatively low investment costs due to inexpensive sensors being used (Gutierrez et al., 2014). Crops grown in this way showed no evidence of health defects due to water shortage. Automated irrigation presents a strong example of the power of automated agriculture, with incredible savings and reduced labor needs.

Automated harvesting. Automating the harvesting process is one of the most difficult obstacles to conquer in precision agriculture. The massive amount of variation in plant types and harvesting methods means that it is difficult to develop one single solution for the problem. Additionally, the modeling and analyzing of 3D plant and tree structures is extremely computationally intensive and time-consuming (Ampatzidis et al., 2017). Crop harvesting automation can effectively be split into two categories: crops that can be harvested whole, such as alfalfa, barley, and sudan, and those that require partial plant harvesting, such as apples, sugar snap peas, and cherries. Most fruits and vegetables fall under the partial harvesting category, with each having a unique harvest method. While automation of whole crop harvesting has been successfully completed, harvesting methods for crops in the other category still need significant research.

Whole crop harvesting. Certain crops are harvested entirely, without the need to carefully separate specific parts of the plant. In these cases, automated harvesting can be accomplished through a self-navigating tractor with a harvesting cutter attached behind. This method has been effectively used on crops like alfalfa and sudan, with an efficiency equal to or exceeding that of a human (Pilarski et al., 2002). The aforementioned Hands Free Hectare Project made use of this method in harvesting of a barley cereal crop (Belton, 2016). While seemingly a simple process to automate, automation of whole crop harvesting is built on the extensive research of self-navigating techniques.

Machine vision-based harvesting. The more difficult challenge in automating harvesting is that of partial plant harvesting, which requires specific harvesting requirements. While different automation methods would be needed for each crop, one interesting case study in machine vision-based harvesting is automation of sugar snap pea harvesting. Few crops are more challenging than sugar snap peas, which are incredibly labor intensive to harvest. While presenting farmers with a high value on the market, there are few mechanized harvesting solutions available. The need for high precision to not damage individual pea pods is challenging, especially with a large variance in the size, color, and even shape of the pods (Tejada, Stoelen, Kusnierek, Heiberg, & Korsaeth, 2017).

Solving this specific problem has been a continual area of research, but breakthroughs in spectral reflectance analysis provide hope for the future of harvesting pea pods. Clear differences in the spectral signatures (the effectiveness of reflecting different wavelengths of light) between pea pods and surrounding leaves are the key to improving upon existing color-based imaging techniques. In order to test the effectiveness of this concept, researchers constructed a small robotic arm, with a grayscale camera attached. In addition, IR LED (Infrared Light Emitting Diode) modules were attached to the arm with a shade covering the entire system to reduce the effects of differing lighting (Tejada et al., 2017). The whole platform was built to be a relatively cost-effective proof of concept, and definite improvements could be made on the individual components used in the system.

The first step in pea pod identification involved illumination of plants with alternating wavelengths of IR light from the mounted LED systems. Since one level of IR light was assumed to reflect better with leaves and stem material, the camera was programmed to take multiple images, overlaying the two and subtracting the stem material. Additionally, adjusting the exposure of the image using a fixed threshold can provide a clearer division of the plant material from pods (Tejada et al., 2017). The resultant index image represents a rough approximation of pea pod location, with pea pods in white and surrounding material in black. A form of ellipse discrimination is then used to approximate the total area of pea pods (Tejada et al., 2017). Pods are assumed to be of a relatively uniform elliptical shape, with varying sizes. White spaces on the image are mapped into elliptical regions, with certain size variance accounted for. Following this processing, the robotic arm can move above identified ellipses and cut the pods from the stems (Tejada et al., 2017).

The effectiveness of this method is impressive but does need improvement before commercial implementation. The camera detection method was 93% accurate in identifying pods, with some issues when leaves obstructed the IR LED light from reaching pods. The cutting accuracy was only 54%, but researchers believe this primarily resulted from the robotic arm’s precision, size, and motion constraints. One of the major issues that this method does not entirely solve is overlapping pea pods, sometimes identifying multiple pea pods as a single large pod (Tejada et al., 2017). While improvements on the robotic arm could be essential for improving cutting technology, a more advanced method of pod identification could be useful as well. Implementing 3D imagery using multiple cameras could resolve some issues with overlap and the blockage of IR light. Other crops requiring similar care in harvesting could benefit from this research, and assist in further automating harvesting for all crops.

Effects of Automation

One of the key considerations when approaching the automation of agriculture and the adoption of digital and precision agriculture techniques is the effect an automated system may have. Human labor, repair of machinery, individual farming style, security, and the environment are all impacted by the increased role of automation in the agricultural sector. While the effects of precision and digital agriculture have not been fully studied, many of them can be predicted or deduced based upon similar automation attempts and the general trends of society.

Role of Labor

Studies on farming in the US have revealed that the use of both land and labor has been decreasing over time as technology is adopted. Farmers increasingly turn to precision and digital agriculture to reduce labor and production costs (Iglehart & Zsofka, 2013). It is important to note that this trend has been consistent, with no sharp declines directly connected to technological developments. The increased efficiency of automated machinery reduces resource constraints on farmers (Bedford, 2018). Farm labor jobs are expected to decrease with the decline of manual labor and increase of automation. The result is increased productivity at the same cost to farmers, resulting in increased stability of food prices.

Beyond direct effects to manual labor on farms, growing automation typically results in a decline of rural life. In many countries with a lack of urban population and job opportunities, reduced manual farming jobs could undermine existing poverty reduction efforts (Fraser & Charlebois, 2016). Since building up urban populations is not an efficient solution to this issue, researching ways to reduce the impact on rural populations is important in these situations.

One interesting solution to this problem has been effectively enacted in the lettuce farming industry in California involving a combination of manual labor with automated machinery. A specialized lettuce harvester makes use of high-pressure water beams in order to cut lettuce heads, at which point lettuce is transported to workers via a conveyor belt. The farm workers are then responsible for tearing off dead leaves and preparing the lettuce for shipment. With many California farms facing labor shortages of 20%, automated technology working in tandem with farm laborers can allow farms to continue to operate with the same output (Simon, 2017). Introducing automation in this way presents major opportunities by sustaining the farming industry in light of a declining workforce. Additional automation could further affect farm labor, but initial introduction in this way would prove extremely beneficial.

Machinery Repairs

One of the major concerns of farmers with regards to the adoption of technologically advanced machinery is how repairs of machinery will change. New machinery and the included computer systems are often proprietary, with self-repair being both difficult and introducing legal liability (Wiens, 2015). As a result, repair costs for a farmer are rarely as simple as buying a part and replacing it by themselves. Instead, farmers are required to hire experienced, often expensive repair technicians. These effects have already been witnessed in many farms with current technology and can be expected to continue with the rise of fully automated machinery.

Farming Style

One additional way that automation affects farming is in the style of individual farmers. Typically, different farmers have different ways they accomplish certain farming tasks and many fear that automation would remove any of these unique differences in style. Similarly, many farmers rely on intuition to determine the time of farming tasks and do not believe that machine learning and data gathering can replace this. Even those farmers who are open to automation see planting as one task that is reserved for them and are reluctant to turn this step over to machinery (Bedford, 2017). Beyond farmers' feelings about automation, many fear the safety of automated machinery roaming on their farms (Gebbers & Adamchuk, 2010). It is important for manufacturers to consider these concerns and find ways to alleviate them.

Security Dangers

Some of the farmers' concerns about the safety of advanced machinery are well founded. Current automated driving technology benefits from complex machine-learning algorithms. A multitude of companies that are developing this technology do not fully understand how it works and as a result have neglected security concerns. Security flaws in software and authentication could lead to disastrous effects if a malicious actor were able to gain control of a vehicle (Garfinkel, 2017). Research must be done on the best ways to secure the computer systems incorporated in machinery including authentication and networking between machines. As this is an area of high impact and currently little development, it is critical that advancements be made before mass production of automated technology.

Environmental Impact

A major benefit of many of the precision agriculture advancements is reduced environmental impact in farming. The utilization of automated herbicide spraying techniques reduces the use of many harmful chemicals on soil (Pringle, 2017). Beyond the immediate effects to soil, water pollution is significantly reduced by automation advancements. Beyond pollution reduction, automated machinery typically weighs less, resulting in reduced soil compaction (Pringle, 2017). Soil that has not been compacted by heavy machinery benefits wildlife populations and also makes it easier for farmers to accomplish plowing and planting tasks. Overall, automated machinery is extremely beneficial for the environment.

Conclusions

Many significant advancements in agricultural automation have been based on emerging computational technology. The ability to collect and analyze large quantities of data on farmland and crops is a major benefit to farmers. Machine vision-based systems are beneficial across multiple stages in agriculture including navigation in fields, weeding, and harvesting. Other farming tasks such as herbicide application and irrigation also show promise for automation with the assistance of computer-based systems. Since a majority of agricultural automation machinery is not commercial or publicly available yet, it is hard to know the exact effects that such technology will have on the industry. On the whole, however, automating the farming process appears to be a net positive for farmers and consumers, and could be the key to feeding a growing population.

References

Ampatzidis, Y., Bellis, L. D., & Luvisi, A. (2017). IPathology: robotic applications and management of plants and plant diseases. *Sustainability, 9*(12), 1010. doi:10.3390/su9061010

Ball, D., Upcroft, B., Wyeth, G., Corke, P., English, A., Ross, P., . . . Bate, A. (2016). Vision-based obstacle detection and navigation for an agricultural robot. *Journal of Field Robotics, 33*(8), 1107-1130. doi: 10.1002/rob.21644

Bedford, L. (2017, November 29). How automation will transform farming. Retrieved from https://www.agriculture.com/technology/robotics/how-automation-will-transform-farming

Belton, P. (2016, November 25). In the future, will farming be fully automated? Retrieved from http://www.bbc.com/news/business-38089984

Corrigan, F. (2018, August 29). Multispectral imaging camera drones in farming yield big benefits. Retrieved from https://www.dronezon.com/learn-about-drones-quadcopters/multispectral-sensor-drones-in-farming-yield-big-benefits/

Fraser, E., & Charlebois, S. (2016, February 18). Automated farming: good news for food security, bad news for job security? Retrieved from https://www.theguardian.com/sustainable-business/2016/feb/18/automated-farming-food-security-rural-jobs-unemployment-technology

Garfinkel, S. (2017, August 22). Hackers are the real obstacle for self-driving vehicles. Retrieved from https://www.technologyreview.com/s/608618/hackers-are-the-real-obstacle-for-self-driving-vehicles/

Gebbers, R., & Adamchuk, V. I. (2010). Precision agriculture and food security. *Science, 327*(5967), 828-831. doi:10.1126/science.1183899

Gutierrez, J., Villa-Medina, J. F., Nieto-Garibay, A., & Porta-Gandara, M. A. (2014). Automated irrigation system using a wireless sensor network and GPRS module. *IEEE Transactions on Instrumentation and Measurement, 63*(1), 166-176. doi:10.1109/tim.2013.2276487

Iglehart, C., & Zsofka, G. J. (2013). *Farming and farmland in the United States: changes and trends*. Hauppauge, NY: Nova Science.

Jørgensen, R., Nørremark, M., Sørensen, C., & Andersen, N. A. (2008). Utilising scripting language for unmanned and automated guided vehicles operating within row crops. *Computers and Electronics in Agriculture, 62*(2), 190-203. doi:10.1016/j.compag.2008.01.009

Kaivosoja, J., Jackenkroll, M., Linkolehto, R., Weis, M., & Gerhards, R. (2014). Automatic control of farming operations based on spatial web services. *Computers and Electronics in Agriculture, 100*, 110-115. doi:10.1016/j.compag.2013.11.003

King, A. (2017). Technology: the future of agriculture. *Nature, 544*, 21-23. doi:10.1038/544s21a

Liu, T., Wu, W., Chen, W., Sun, C., Zhu, X., & Guo, W. (2015). Automated image-processing for counting seedlings in a wheat field. *Precision Agriculture, 17*(4), 392-406. doi:10.1007/s11119-015-9425-6

Merfield, C. N. (2016). Robotic weedings false dawn? Ten requirements for fully autonomous mechanical weed management. *Weed Research, 56*(5), 340-344. doi:10.1111/wre.12217

Nan, L., Chunlong, Z., Ziwen, C., Zenghong, M., & Zhe, S. (2015). Crop positioning for robotic intra-row weeding based on machine vision. *International Journal of Agricultural and Biological Engineering, 8*(6), 20-29. doi:10.3965/j.ijabe.20150806.1932

Pilarski, T., Happold, M., Pangels, H., Ollis, M., Fitzpatrick, K., & Stentz, A. (2002). The Demeter System for automated harvesting. *Autonomous Robots, 13*(1), 9-20. doi:10.1023/a:1015622020131

Pringle, R. (2017, October 02). Drones, tractor hacks and robotic sprayers: The technology of farming. Retrieved from https://www.cbc.ca/news/technology/farming-technology-advances-1.4290569

Rejcek, P. (2017, October 30). The farms of the future will be automated from seed to harvest. Retrieved from https://singularityhub.com/2017/10/30/the-farms-of-the-future-will-run-on-ai-and-robots/

Simon, M. (2017, May 31). Robots wielding water knives are the future of farming. Retrieved from https://www.wired.com/2017/05/robots-agriculture/

Srbinovska, M., Gavrovski, C., Dimcev, V., Krkoleva, A., & Borozan, V. (2015). Environmental parameters monitoring in precision agriculture using wireless sensor networks. *Journal of Cleaner Production, 88,* 297-307. doi:10.1016/j.jclepro.2014.04.036

Srininvasulu, P., Sarath, M., & Venkat, R. (2016). Automated services for agro-farms using Internet of Things (IoT). *International Journal of Computer Applications, 154*(11), 17-20. doi:10.5120/ijca2016911864

Tejada, V. F., Stoelen, M. F., Kusnierek, K., Heiberg, N., & Korsaeth, A. (2017). Proof-of-concept robot platform for exploring automated harvesting of sugar snap peas. *Precision Agriculture, 18*(6), 952-972. doi:10.1007/s11119-017-9538-1

Wiens, K. (2015, February 05). New high-tech farm equipment is a nightmare for farmers. Retrieved from https://www.wired.com/2015/02/new-high-tech-farm-equipment-nightmare-farmers/

Young, M. (2018). The age of digital agriculture [PDF]. Retrieved from https://s3-us-west-2.amazonaws.com/climate-com/images/the-age-of-digital-agriculture.pdf