www.tibm.org.tw

Journal of Biomechatronics Engineering
Vol. 1, No. 1, (2008) 37-54

A review of automation and robotics for the bio-industry

Tony Grift [a, *], Qin Zhang [a], Naoshi Kondo [b], K.C. Ting [a]

[a]*Department of Agricultural & Biological Engineering, University of Illinois, Urbana-Champaign, 360J Agricultural Engineering Sciences Building, 1304 West Pennsylvania Avenue, Urbana, IL 61801, USA.*

[b]*Kyoto University, Kyoto, Japan.*

Abstract

Automation technology research in agriculture is proliferating throughout the globe. There are several trends that drive the application of automation technology in agriculture. Firstly, by the year 2042, the world population is projected to increase to 9 billion souls. There will be a huge challenge in providing abundant high quality, affordable, safe and nutritious foods for such population, especially in light of the trend to use arable land for bio-fuel production. Secondly, the labor force in agriculture is declining and automation technology can be used to replace some traditional labor. For instance, in specialty crop production labor is often tedious, non-ergonomic and carried out by unskilled personnel. Automation technology can improve the productivity, health and job-satisfaction of personnel, but there are serious technical challenges in automating operations especially in horticulture and viticulture. Thirdly, the environmental impact of Agricultural production needs to be limited. For instance, today worldwide seven weed species have been identified as being resistant to glyphosate. The only truly sustainable solution for this problem is high-speed mechanical weed control which is under development. Although automation technology holds ample promise for the future, currently the overall performance of the machines is often insufficient to compete with traditional methods. The limited performance of the machinery is one of the reasons why to date few of the technologies developed have been commercialized. However, the role of automation technology will increase and its impact on agriculture as we know it will be profound. This paper describes agricultural automation research in areas that typically constitute automated systems, being 1) Sensing and perception, 2) Reasoning and Learning, 3) Data Communication and 4) Task planning and execution. A separate section is devoted to Robotics

* Corresponding author. Tel.: +1 (217) 333-2854; fax.: +1 (217) 244-0323.
E-mail address: grift@uiuc.edu (T. Grift)

applications within plant production, animal husbandry, controlled environment as well as field robotics.

1. Introduction

The development of agriculture in traditional hunter-gatherer societies started around 10,000 years ago and has been crucial to the formation of human civilizations across the globe. Over the centuries agriculture has morphed into the modern large-scale bio-industry it is today, producing goods through the growing of plants, animals and other organisms in close interaction with the environment. The major changes in agriculture have occurred through domestication of crops and animals, weed control techniques, water management, fertilizer/pesticide application, genetic engineering and the large-scale mechanization that occurred in the middle 1990's. Although the improved methods and techniques over time have resulted in a global system capable of feeding 6 billion souls, it has also caused major concerns regarding its impact on the environment. In addition, owing to the recent worldwide attention to energy security as well as climate change, agriculture is projected as the supplier of bio-energy from renewable sources, opening up a new realm of opportunity and responsibility. Some of the issues facing agricultural production today include (1) managing and utilizing resources in the production while ensuring a sustainable natural environment; (2) laborious operations under conditions not conducive to human productivity; (3) advancement of technologies in other industries that threaten to attract labor force away from agriculture; (4) an increased demand for higher product quality; (5) the necessity to modernize agriculture using technology; (6) the trend towards organic farming and (7) to employ human intelligence and machine power in a sustainable and economical manner. The application of automation technology plays a role in all these issues: It can contribute to sustainability by providing field information through sensing, and to offer optimization tools. Robots are being developed to replace manual labor in the harvesting of fruits and vegetables. Weeding robots can replace chemical herbicide application in organic farming. Automation technology inherently addresses the issue of a dwindling labor force. The current plant factories in Japan produce high quality vegetables, free of disease or insect damage and are run with little human intervention. It is evident that automation technology is a field that can offer significant benefits to producers and consumers in the near future.

Before addressing the (potential) applications of automation in agriculture it is useful to state a definition: The term automation signifies the added quasi-anthropomorphic intelligence to mechanized processes and/or devices (Ting, 1997). The capabilities of intelligence-enabled machines include: (1) Sensing and perception– obtaining the awareness of surroundings; i.e., gathering, processing, and interpretation of information about situations, (2) Reasoning and learning – conducting logical deduction, mathematical analysis, heuristic inference, and experiential adaptation used to derive conclusions, make decisions, and issue instructions, (3) Communication – coordinating and delivering information among various entities (4) Task planning and execution –

effecting device operations for control activation and physical work. Commonly seen additional components are external sensing, transporting, and traveling devices (Kondo and Ting, 1998).

This article provides a review of past and current research and development in automation technology for the bio-industry.

2. Sensing and perceptions

The aim of agricultural production managers is to optimize crop yield and consequently profit. Therefore, the crop needs to be protected against common biotic stresses such as diseases, insect infestations, and competition from weeds as well as a-biotic factors such as nutrient and water stress. Precision crop nutrition management has been the traditional tool to achieve optimized yield and it requires accurate and reliable information about the soil and crop conditions.

Important soil parameters that need to be measured are moisture level, nitrogen level, pH, compaction levels and organic matter content. Ehsani et al. (1999) developed a Near Infrared (NIR) based technique to measure the nitrogen content of the soil. To assess the depth and strength of a compaction layer Grift et al. (2005a) developed an acoustic method in a laboratory setting and Adamchuk et al. (2001) developed a strain gage based method to measure soil mechanical impedance. Electrical Conductivity (EC) has been used extensively as a proxy measurement for soil fertility which is related to organic matter (Fraisse et al., 2001; Mueller et al., 2003). EC sensors in combination with pH sensors are commercially available.

In standing crops there is a need to measure and assess nutrition level, disease and pest infestations, bacterial/viral infections, overall plant health and the proliferation of weeds. Among these, weed proliferation monitoring is easiest: it can be based on morphological properties, such as shape, size and color using cameras. CCD (charge coupled device) cameras have been applied successfully for detecting weeds in soybean fields (Tian, 2002) and in cotton fields (Downey et al., 2003). In weed management, there are currently two schools of thought being weed detection, where the crop plants are detected and all other plants are considered weeds and weed identification. The latter is becoming increasingly important, since there are currently several weed species that have shown resistance to glyphosate, the main ingredient in 'Roundup', a popular herbicide in the United States. The most threatening resistant species is common waterhemp (Amaranthus rudis) and tall waterhemp (A. tuberculatus), collectively referred to as waterhemp. This species has shown resistance to protoporphyrinogen oxidase (PPO)-inhibiting herbicides as well as ALS-inhibiting and triazine herbicides (Patzoldt et al. 2005). This waterhemp biotype uses a unique mechanism of resistance to survive exposure to PPO herbicides (Patzoldt et al. 2006). For weed identification algorithms are used such as artificial neural networks (ANNs), (Burks et al., 2000) genetic algorithms (Tang et al., 2000) and wavelets (Tang et al., 2003). The emergence of weeds that exhibit resistance to herbicides will require the development of high-speed mechanical in-row weed control technology which is in development. On-board imaging systems have also been used for plant counting to accurately estimate the corn population in an early growth stage (Shrestha and Steward, 2003).

The use of multispectral-image-based perception methods has been studied extensively to assess the crop nutrition level based on crop canopy reflectance in multiple spectral bands (Kim et al., 2000; Sui et al., 2005). Remote sensing, which uses multi and hyper-spectral imagery originating from satellites (Yang et al., 2004); airplanes (Yao and Tian, 2004) or helicopters (Sugiura et al., 2002), has been used to assess crop nutrition stress. After comparing the Normalized Difference Vegetation Index (NDVI) calculated using both satellite- and aerial-based crop canopy images Han et al. (2002) found that both methods were highly correlated to ground truth data when crop conditions were relatively heterogeneous across a field. When the crop conditions were more uniform, the correlation decreased significantly. Though aerial and satellite imageries are useful for research, both require extra expense to farmers since up-to-date images must be purchased annually. Alternatively, on-board systems are in development that can provide the farmer with up-to-date imagery in time and space. Kim et al. (2000) and Noh et al. (2005) developed on-board systems for real-time detection of nitrogen concentrations in corn plants to enable variable-rate fertilization. Both systems were based on NDVI estimation in terms of light reflectance intensity on leaves in various spectral bands. Reum and Zhang (2007) describe an innovative approach enabling more sensitive detection of crop nutritional stress levels. They represented the reflectance of corn leaves images in terms of a one-dimensional intensity distribution pattern in specific signal bands, after which they applied a wavelet transform to map the resulting patterns to various crop nutritional stress levels. This method offers a more accurate crop nutrition level perception since it is capable of making such an assessment based on individual plant data.

Crop diseases require early detection to prevent potential widespread crop losses. The difficulty in detecting infections at an early stage also results in excessive use of pesticides and increased production costs (Sasaki and Suzuki, 2003). Conventional detection of disease infection is based on visual inspection, which is often too late to prevent damage. With the increased application of optical sensing technologies in agriculture, researchers have attempted various approaches to detect crop diseases and viral infections at an early stage. One of such approaches is the measurement of radiation reflectance intensity from plant leaves over a wide spectrum. This method is based on the fact that many kinds of diseases and viral infections cause a change in optical reflectance properties of the leaf surface, often resulting in an increase of reflectance in the visible bands (West et al., 2003). Examples of disease and virus infections using this approach include detection of Puccinia striiformis in wheat (Bravo et al., 2003), the Botrytis fabae (Chocolate spot disease) fungus infection in field beans (Malthus and Madeira, 1993), and Late Blight in tomatoes (Wang et al., 2008). Other commonly used crop disease sensing technologies include fluorescence and thermal imaging, which can extend and improve the capability of various crop disease sensing techniques.

Arguably the largest number of CCD based cameras is applied in the product quality inspection stage. In a recent citrus fruit grading system, 6 color cameras were applied to measure color, size, shape, and defects on the top, bottom, and 4 lateral sides of a fruit

(Njoroge, et al., 2002). Near infrared (NIR) inspection has been used to enhance the fruit market value because it can determine not only sugar and acid contents but also internal qualities such as rotten core, black heart, maturity, tannin, and cavity (Lu and Ariana, 2002). In addition, X-ray imaging systems have been used to inspect internal structural defects such as rind-puffing and the granulation status of the juice sacs (Njoroge, et al., 2002). Recently, X-ray sensors were also used for kiwi fruits, apples, pears, peaches, persimmon, potatoes, melons and other fruits (Tao et al., 1990; Miller and Delwiche, 1991; Kondo, 2003). To measure the degree of gloss on whole eggplant fruit surfaces, 10 cameras (6 color and 4 monochrome) were installed in a grading facility at Okayama, Japan (Kondo et al., 2007a).

Proper lighting is an essential component of any machine vision system. Since bio-products have varying optical characteristics in various spectra, many types of imaging techniques and devices have been developed, from the visible region to X-ray, UV, and infrared regions. The latest technologies use Terahertz (THz) imaging through the development of new light sources and detectors (Hu and Nuss, 1995; Kawase et al., 2003). In addition, nuclear magnetic resonance (NMR) technology has been also applied to bio-products (Chen et al., 1989; Song and Litchfield, 1990; Wang et al., 1988). Whereas hyper-spectral images are effective for food quality and safety monitoring, fluorescent imaging can aid in the detection of defects in fruits, plants, and meats (Bodria et al.,2002; Kim et al., 2001; Kim et al, 2004; Kondo et al, 2007b).

Another application of optical perception technology is the guidance of robotic equipment. In the early 1980s, a research team at Michigan State University, USA, studied the potential of acquiring tractor guidance information from field images by evaluating several image processing techniques (Gerrish and Stockman, 1985). Their effort led to the development of a vision-guided tractor capable of following straight crop rows with an accuracy of 6 to 12 cm (Gerrish et al., 1997). In the same period, a Texas A&M University, USA, research team investigated a novel approach of steering a tractor following both straight and curved row crops. It demonstrated through field tests that their algorithm could detect heading errors within 0.5° and offset errors of less than 5 cm (Reid and Searcy, 1986). In the late 1990s, a team of the University of Illinois, USA, developed a research program on path perception technologies for autonomous agricultural equipment. Some of the early achievements included the use of redundant navigation sensors by fusing machine vision sensing with GPS and inertial sensor data. The combination of sensors provided reliable navigation information for guiding agricultural equipment performing various field tasks at normal operation speeds. Vision-based path perception was used to guide agricultural tractors performing field operations at speeds of up to 17 km/h on straight rows and up to 10 km/h on curved rows (Zhang et al., 1999; Will et al., 2000; Han et al., 2004. The sensor fusion-based path finder methods for guiding agricultural equipment all achieved a tracking accuracy of 2.5 cm at typical speeds (Han et al. 2003; Zhang and Qiu, 2004). To improve the accuracy of object localization within the perceived scene under quickly varying light conditions, the research team also successfully used stereovision for to guide tractors performing field operations (Rovira-Más et al., 2004; Kise et al., 2005a). Benson et al., (2003) demonstrated a vision-based guidance system that uses the edge of the cut-uncut crop for guidance of a combine harvester at normal operating speeds.

Some other advancements on robotic equipment navigation perception technology researches include the work reported by Subramanian et al. (2006) who used a monocular camera to observe citrus grove alleyways, and Nara and Takahashi (2006) who applied a vision system to detect obstacles. However, little has been reported on using vision-based navigation to guide agricultural vehicles traveling in an open field without structured crops as landmark references. The challenge in using visual sensor to navigate a vehicle traveling on an open terrain is to find and utilize landmark points from unknown and randomly present textures. In contrast there are examples of guiding robotic vehicles on planetary-like terrains (Gonzalez-Barbosa and Lacroix, 2002), on urban streets (Saeedi et al., 2006), and agricultural fields (Wang and Zhang, 2007). In most of these researches, stereo cameras were used to perceive the environment because of their ability to provide 3D information. Furthermore, stereovision has important advantages for robotic equipment navigation in a natural environment, including moderate insensitivity to shadows and lighting changes and the capability to detect obstacles.

To navigate autonomous vehicles in fields, in addition to optical sensors, laser range finders have been used. To navigate an autonomous vehicle between tree rows, Barawid et al., (2007) reported on the successful development of a laser range finder based guidance system, using the Hough transform to recognize the trees. Laser range finder technology was also used as a real-time collision avoidance sensor in agricultural fields (Kise et al., 2005b). Lee and Ehsani (2008) investigated the accuracy of two common laser range finder units.

3. Reasoning and learning

The Internet has made information sources readily available, but the question how to use information intelligently is still a major research interest. In order to enable intelligence empowered bio-production systems, capabilities are required for automated data processing, logical/mathematical/heuristic reasoning, and experiential learning. Commonly seen machine reasoning and learning processes are in the forms of computer models, expert systems, artificial neural networks and decision support systems (Fang et al., 1992; Humphreys et al., 1994; Chao and Ting, 2003; Fleisher et al., 2002). Systems informatics and analysis is the branch of science and engineering that develops tools to gather, store, retrieve, analyze, present, and interpret information to aid in the process of decision-making (Snow and Lovatt, 2008; Körner and Van Straten, 2008; Matthews et al., 2008). A system is a set of interrelated components organized to achieve certain goals. The systems paradigm emphasizes the performance of a system as a whole through understanding all components in the system, as well as the interrelationships among the components (Lejars et al., 2008). The importance of the systems approach arises from the fact that (1) individually functioning components do not necessarily constitute a working system, (2) piece-wise knowledge about individual components does not automatically provide a complete understanding of the overall system, and (3) necessary yet missing components can be detected after observing/analyzing the system as a whole.

The challenges in the integration of scientific information are as follows: (1) Many scientists have been very successful within their well defined disciplinary boundaries and it is not clear to individual scientists, why active participation in the effort of information integration is of any value; (2) the concept of systems analysis has not received the attention it deserves in the agricultural research community and the mechanism of systems analysis is perceived as frightening; (3) the tools used for systems analysis are mostly not user-friendly and incapable of dealing with dynamically changing information bases in a real-time fashion; (4) the integration of information from traditionally unrelated fields, such as life science and engineering, is likely to encounter new challenges; (5) the assumptions of systems analysis and methods of handling uncertain and incomplete information are not transparent; (6) it is difficult to balance "analysis" and "action" (Ting et al., 2003).

In order to successfully address the issues and solve the problems associated with agricultural production systems, core competencies of automation, culture, environment, and systems (i.e., the ACESys paradigm) are required. The culture (i.e., biosciences and biotechnologies) and environment set the governing conditions under which agricultural operations take place. Automation deals with information processing and task execution, and often plays the role of integrator for a functional system. Automation adds to machines the quasi-anthropomorphic capabilities of perception, reasoning & learning, communication, and task planning & execution. Systems analysis and integration is a methodology that starts with the definition of a system and its goals and leads to the conclusion regarding the system's workability (i.e., technical feasibility and practicality), productivity, economic viability, reliability, and other performance indicators for decision support purposes. Computers, with their vast storage capacities for data and algorithms and high-speed information processing, have brought about ever increasing possibilities for effective automation, with high precision, for agricultural systems (Ting, 2000).

The ACESys concept is very useful in determining the "abstraction" (in the forms of foundation classes representing objects of interest) and information flows for bio-production systems. This systems abstraction technique may be applied to any bio-production system. The resulting foundation classes may represent the system components in as much breadth and depth as needed. The major difference will be the "culture" classes and objects. For example, if a controlled environment plant production system is under study, objects and classes that describe plant biological characteristics and processes will need to be developed and incorporated in the appropriate automation and environment (Fleisher et al., 1999; Ting and Sase, 2000).

4. Data communication

Communication technology is an essential component of automation in agriculture since it provides information flows among intelligent machines and human interfaces (Zhang and Ehsani, 2007). The convergence of sensing, computing and communication technologies for agricultural applications can be termed an 'agricultural infotronics systems' (AIS), essentially a real-time network topology connecting all on-farm production data management systems (Zhang et al., 2000).

In-vehicle communication has been standardized in the Controller Area Network (CAN), a serial two-wire multi-node message broadcast system with a maximum signaling rate of 1 Mbit per second. CAN is now common on many types of agricultural machinery, and the data communication protocol used is ISOBUS, standardized in ISO 11783. An overview of the Controller Area Network can be found in Etschberger (2001) and Benneweis (2005) provides an overview of the status of the ISO 11783 standard. Although there is great interest in inter-vehicle communication to optimize the performance of machines working in cooperative systems such as in large-scale harvesting operations, there is no communication standard available for this purpose.

Wireless data communication can be implemented using the common Local Area Network (LAN) such as WiFi (IEEE 802.11.b), or a Personal Area Network (PAN) such as BlueTooth (IEEE 802.15.1), a low-power, short-range wireless industry standard often used to connect sensors to Electronics Control Units (ECUs) within a short range (Zhang and Ehsani, 2007; Kim et al., 2006). A strong alternative to the short-range BlueTooth is Zigbee (IEEE 802.15.4) and Zigbee Pro, the latter having an outdoor range specification of 1500 m. Since Zigbee is a multi-node network the range can be extended indefinitely by using intermediate nodes and information relay nodes. Zigbee is currently used in viticulture for distributed data acquisition (Morais et al., 2008) as well as animal tracking (Nadimi et al., 2008). An overview of Zigbee wireless data communication technology is given in Hebel, (2007). Another class of wireless data communication devices is Radio Frequency Identification (RFID). These devices consist of small tags which are used for human, animal and product tracking applications (Sahin et al., 2002). A complete overview of wireless sensor applications in agriculture and food industry is given in Wang et al., (2006).

5. Task planning and execution

Task planning and execution are essential functions of a highly automated machine. For instance, an assembly robot with an arm and gripper needs to have enough intelligence to automatically synthesize a manipulation plan when presented with randomly oriented parts (Tung and Kak, 1996). In agricultural robot applications the planning and execution task are usually far more complicated than their counterparts in industrial robotics, since the objects to be handled are usually unstructured and presented in random locations such as in cucumber harvesting (Van Henten et al., 2003). Similarly, in field robotics, an autonomous weeding robot has a set of actions it can perform to move itself around a field such as ‘turn left’,’backup’, and ‘extend effector’. To perform an overall task such as weeding, the robot must follow a sequence of subtasks in a certain order. This order may be fixed or adaptive: In the latter case the order must be decided by an intelligent algorithm that takes into account the environment through sensors and plans tasks according to a certain optimization criterion. Jorgensen et al. (2008) showed planning algorithms written in a scripting language to guide a weeding robot in a realistic field. Greenhouse control is another area where task planning is needed to achieve goals such as a target harvest date (Albright, 1990).

6. Robotics

Robotics in Agriculture is not a new phenomenon: In controlled environments it has a history of over 20 years. However, with the latest increase in computational power combined with a cost reduction, robotics applications are spreading. For convenience, we will categorize the applications in plant oriented robotics, animal robotics, controlled environment robotics (green houses) as well as field robotics.

6.1. Plant production

The study of agricultural robot application for plant production presumably started with a tomato harvesting robot (Kawamura et al., 1984). Currently there are automated harvesters in the research phase for cherry tomatoes (Kondo et al. 1996a), cucumber (Van Henten et al., 2002), mushrooms (Reed et al., 2001), cherry (Tanigaki et al., 2008) and other fruits (Kondo et al., 1996b). In horticulture, robots have been applied to harvest citrus (Hannan and Burks, 2004) and apples (Bulanon et al., 2001). So far, no harvesting robot has reached the stage of commercialization, because of their low operation speeds, low success rates, and high costs. A recent robot which is the closest to commercialization may be a strawberry harvesting robot (Kondo et al., 2005). The robot operates during night time and harvests fruits hung from the sides of a table top culture in approximately 20 second, yielding a harvest capacity of 0.3 ha greenhouse per night.

In seedling production, there are many operations such as seeding, thinning, grafting, cutting sticking, transplanting, and others. Some of them are automated and robotized, while some robots have been commercialized with cell trays in the 1990s. A seedling transplanting system was developed (Ting et. al., 1990a) based on a 4 Degree Of Freedom (DOF) SCARA robot and a sliding-needle type end-effector (Ting et. al., 1990b). Later Yanmar Co., Ltd., Japan started selling a four fingered robotic transplanter which transplants seedlings from a cell tray to pots using a Cartesian coordinate manipulator. Visser company, the Netherlands also produces a type of transplanting robot which uses machine vision and end-effectors to replace defective seedlings. The former and the latter robots have capacities of handling 6000 seedlings/h and 4500 seedlings/h respectively.

The 'cutting/sticking' operation is often conducted for seedling propagation where individual leaves are cut from the mother plant, and placed inside a tray in which they grow to full plants. A chrysanthemum cutting/sticking robotic system consisting of machine vision and a manipulator was developed at Okayama University (Kondo and Monta, 1997). Based on the experimental results, a fully automatic model and a semi-automatic model for commercialization were developed by Panasonic company and Iseki Co., Ltd. The fully automatic robot was capable of sticking a cutting in 5 to 6 seconds. Another type of cutting/sticking robot was developed for geranium at the University of Georgia, USA (Simonton and Pease, 1990).

The grafting operation ensures higher quality production and disease resistance to seedlings. Although a semi-automatic grafting robot which could process 800 cucumber seedlings was commercialized by many companies 15 years ago (Kondo and Ting, 1998), two operators were required to service the robot, and it is desirable to fully automate the operation.

The ‘plant factory’ arguable constitutes the pinnacle of automation technology in plant production. It is a highly automated facility where vegetables and fruits can be produced with minimal human intervention in an environment free of disease, insects and the risk of mechanical damage. Mitsubishi Heavy Industry Company and Kyushu Electric Company (Mitsuhashi et al., 1994) attempted to build a fully automated plant factory which contained automatic machines and environments for seeding, germination, seedling nursery, transplanting, seedling spacing, harvesting and packaging. The production sequence was as follows: A seeding device places coated seeds into twelve holes of a urethane cube shaped by a cutting device. The seeded tray is then transported to a germination platform where it is irrigated at regular intervals. After germination, the seedling is transported to a nursery platform where it is grown under controlled artificial lighting in a hydroponic solution. When the seedling has matured sufficiently, a transplanting device picks up the urethane cube with the seedling and places it into a growing bar using four fingers. This growing bar method was adopted so that the space among the seedlings can be varied in relation to the growth stage of the seedlings. When the seedling has grown to full maturity, the growing bars are transported to the harvesting machine, which cuts the roots after which the plants are weighed and wrapped in a film.

The capacity of the system is equivalent to four operators, because the devices in the system can work for a total of 33 person hours a day, where the system produces 1500 vegetables per day. The breakdown of the 33 hours is 8% for seeding, 12% for transplanting, 27% for spacing, 30% for harvesting and wrapping, 11% for washing materials and equipment, 9% for shipping, and 3% for seedling nursery. 77% of the 33 hours is automated, while the remaining 23% for the latter three items is conducted manually (Kondo and Ting, 1998).

6.2. Animal husbandry

Milking is the most laborious task in dairy cattle husbandry. In The Netherlands, two types of robot milking systems are on the market (Kuipers, 1996). In both systems the robot is stationary the cows have to visit a milking box where they are milked and fed simultaneously. The attachment of teat cups in one system was based on teat locations stored a priori in a computer, combined with a vision system and the teat cups were attached simultaneously. The other system employed a robotic arm that was positioned below the udder and ultrasonic sensors were used to determine the locations of the teats. After these locations are determined, the teat cups are attached individually (Hogewerf et al., 1992). There are currently companies selling the milking robots in The Netherlands, Germany, Sweden, USA, and Japan. Developmental research on autonomous milking systems for stanchion barns has been conducted as well (Hachiya et al., 1996). In this system the animals remain stationary while the milking robot moves along a gantry system.

To reduce the cost of wool harvesting, two types of wool shearing robot systems were developed at the University of Western Australia (Trevelyan, 1992) and at the Australian Wool Corporation (Australian Wool Corporation, 1988). Since sheep are easily damaged animals, a fast response and high reliability of the robot are required to avoid damage to the sheep's skin. In one robotic shearing system, the sheep were held on trolleys which were automatically moved to one of the shearing stations. The robot's computer was programmed with sheep morphology and at every shearing operation the morphological map was updated. The robot could shear 95% of a sheep in 24 minutes. The other robot system consisted of dual manipulators for higher working efficiency. Although the shearing time per sheep was reduced to 1.5 min which is 1/5 of a human operation, this robot only sheared the back of the sheep and the remaining areas were sheared manually.

6.3. Controlled environment

In controlled production environments automation technology already has a history of over 20 years. Citrus fruit grading systems (Njoroge et al., 2002) have been equipped with machine vision and NIR internal quality inspection technologies. Later, a fruit grading robot was developed by SI Seiko Co., Ltd. for peaches, pears, apples, and tomatoes (Kondo, 2003). This system consists of two 3 DOF Cartesian coordinate manipulators with 12 sets of suction cups, 12 cameras with 12 sets of lighting devices and can inspect three fruits per second. A packing robot to transport fruits from carriers on a line to a shipping container works in unison with the grading robot.

6.4. Field robotics

Field robotics to date has mainly focused on data collection for weed control. An overview of the activities in weed control is given in Slaughter et al. (2008). The development of robots for field crop production applications is still in its infancy and hence, few articles are available. Baerveldt and Astrand (1998) developed a rudimentary robot targeted for weed control. Bak and Jakobsen (2004) proposed a small field robot capable of traveling between crop rows to register the locations of crops and weeds using a camera and GPS receiver. Hofstee et al. (2004) developed a machine vision based algorithm for autonomous crop guidance. Grift et al., (2005b) developed two robots for field scouting applications. There are currently two agricultural Field Robotics student competitions, one in Europe (Van Straten, 2003) and another in the USA.

7. Conclusions

This paper gives a broad overview of automation technology applied in the bio-industry. To speculate about the future impact of automation technology in the bio-industry, it is worthwhile attempting to analyze the forces driving and inhibiting automation research and application.

- The increase in the price of food and commodities is driven by the replacement of arable farm land to produce bio-fuels instead of food. Worldwide there are outbreaks of riots in places where food is available, yet unaffordable. Although there is a definite need to replace the widespread use of fossil fuels with sustainable alternatives, it can not come at the price of poverty. The shortage of fossil fuels also has made fertilizer far more expensive, which is currently offset by the increased prices of commodities. Automation technology can help in making food production more efficient by minimizing inputs and maximizing outputs.

- Organically, grown food is currently relying on abundant manual labor, especially in weeding since no chemical control is allowed. Here autonomous high-speed mechanical weeding alternatives need to be developed. One of the biggest challenges here is to achieve sufficient field capacity and limit energy usage. Multiple robot systems (termed swarms or flocks) may be the solution to this problem.
- The harvest of fruits, vegetables and other specialty crops is often carried out by seasonal labor under harsh conditions. By replacing this tedious labor with automated machines it is possible to eliminate these tasks and offer more rewarding jobs to current laborers. Although research in fruit harvesting has been attempted for decades, a commercial automated system has yet to become available.
- Since in many countries the available labor force in agriculture is decreasing, automation and robotics research can help keeping production up and costs down. A good example are milking robots which have shown to reduce labor requirements as well as offering a more animal friendly environment, since the cows can choose to be milked at will. The plant factories in Japan are other examples where labor can be dramatically reduced and a high quality product is delivered albeit at a high cost due to the housing, lighting and handling requirements.
- The current system of farming is not sustainable. A good example is the emergence of glyphosate resistant weeds. Even if a new chemical would be developed at astronomical costs, in a few decades inevitably new weeds will become resistant. The only long term solution is high-speed mechanical weed control which can be implemented using automation technology.
- Forces inhibiting the research in and commercialization of automation technologies are:
- There are major technical challenges in automation due to the uncontrolled outdoor environment in combination with the fact that agricultural products and materials are highly inconsistent in shape and size. Many attempts to replace human labor by robots carrying cameras to replace human eyes have shown notoriously slow.
- Collaboration among academic institutions and commercial entities has shown cumber some. Many universities in the USA now have research parks where companies work together with academic personnel. This type of collaboration is complicated mainly since the academic world has different objectives such as knowledge gathering and dissemination, whereas companies are interested in Intellectual Property and short development turnaround. Another discrepancy is that in companies time is limited, and budgets high, which is exactly opposite in academics research.
- Funding from government sources is limited, since the perception exists that major manufacturers will develop the technology, and the market mechanism will proliferate it. This is a misconception, since companies will only work on technologies that are applicable in the short term whereas the in-depth long term high-risk research takes place at universities.

- There is the fear among farmers and the general public that automation will take away jobs, that it will remove the romantic aura of farming and that it will impact the recreational value of farm land.
- There are already many striking examples of the benefits that automation technology offers, and they have to be used to convince policymakers that more funds are needed to develop solutions to the problems facing the world today.

References

Adamchuk, V. I., Morgan, M. T., Sumali, H., 2001. Application of a strain guage array to estimate soil mechanical impedance on-the-go. Transactions of the ASAE 44, 1377-1383.

Albright, L. D., 1990. Environment control for animals and plants. American Society of Agricultural Engineers, St. Joseph, Mich, United States, p. 410.

Baerveldt, A., Astrand, J. B., 1998. Vision-guided mechanical weed-control. Halmstad University. Available at: http://www.hh.se/staff/bjorn/mech-weed/. Accessed May 8, 2008.

Bak, T., Jakobsen, H., 2004. Agricultural robotic platform with four wheel steering for weed detection. Biosystems Engineering 87, 125-136.

Barawid, O. C., Mizushima, A., Ishii, K., Noguchi, N., 2007. Development of an autonomous navigation system using a two-dimensional laser scanner in an orchard application. Biosystems Engineering 96, 139-149.

Benneweis, R. K., 2005. Status of the ISO 11783 serial control and communications data network standard. ASAE Paper No.051167, St. Joseph, Mich.

Benson, E. R., Reid, J. F., Zhang, Q., 2003. Machine vision-based guidance system for agricultural grain harvesters using cut-edge detection. Biosystems Engineering 86, 389-398.

Bodria, L., Fiala, M., Oberti, R., Naldi, E., 2002. Chlorophyll fluorescence sensing for early detection of crop's diseases symptoms. ASAE Paper No. 021114, St. Joseph, Mich.

Bravo, C., Moshou, D., West, J., McCartney, A., Ramon, H., 2003. Early disease detection in wheat fields using spectral reflectance. Biosystems Engineering 84, 137-145.

Bulanon, D. M., Kataoka, T., Ota, Y., Hiroma., T., 2001. A machine vision system for the apple harvesting robot. Agricultural Engineering International: the CIGR Journal of Scientific Research and Development. Manuscript PM 01 006. Vol. III.

Burks, T. F., Shearer, S. A., Gates, R. S., Donohue, K. D., 2000. Backpropagation neural network design and evaluation for classifying weeds using color image texture. Transactions of the ASAE 43, 1029-1037.

Chao, K., Ting, K. C., 2003. Neural networks. Encyclopedia of Agricultural, Food, and Biological Engineering, pp. 691-696.

Chen, P., McCarthy, J. M., Kauten, R., 1989. NMR for internal quality evaluation of fruits and vegetables. Transactions of the ASAE 32, 1747-1753.

Downey, D., Giles, D. K., Slaughter, D. C., 2003. Ground based vision identification for weed mapping using DGPS. ASAE Paper No. 031005, St. Joseph, Mich.

Ehsani, M. R., Upadhyaya, S. K., Slaughter, D., Shafii, S., Pelletier, M., 1999. A NIR technique for rapid determination of soil mineral nitrogen. Precision Agriculture 1, 217-234.

Etschberger, K., 2001. Controller Area Network. IXXAT Press, Germany.

Fang, W., Ting, K. C., Giacomelli, G. A., 1992. Computer software development for greenhouse design and management. In: Proceedings of the 4th International Conference on Computers in Agricultural Extension Programs, ASAE, Orlando, FL, USA, January 28-31, 1992, pp. 274-279.

Fleisher, D. H., Ting, K. C., Giacomelli, G. A., 2002. Decision support software for phytoremediation systems using rhizofiltration processes. Transactions of the CSAE 18, 210-215.

Fleisher, D. H., Ting, K. C., Hill, M., Eghbali, G., 1999. Top modeling of biomass production component of ALSS. In: Proc. The 29th International Conference on Environmental Systems Paper No. 1999-01-2041, Denver, CO.

Fraisse, C. W., Sudduth, K. A., Kitchen, N. R., 2001. Delineation of site-specific management zones by unsupervised classification of topographic attributes and soil electrical conductivity. Transactions of the ASAE 44, 155-166.

Gerrish, J. B., Fehr, B. W., Ee, G. R. V., Welch, D. P., 1997. Self-steering tractor guided by computer-vision. Applied Engineering in Agriculture 13, 559–563.

Gerrish, J. B., Stockman, G. C., 1985. Image processing for path-finding in agricultural field operations. ASAE Paper No. 85-3037. St. Joseph, MI, June 23-26, 1985.

Gonzalez-Barbosa, J. J., Lacroix, S., 2002. Rover localization in natural environments by indexing panoramic images. In: Proc. 2002 IEEE International Conference on Robotics and Automation, Vol. 2, Washington, DC, pp. 1365-1370.

Grift, T. E., Kasten, M., Nagasaka, Y., 2005b. Robotics in agriculture: Asimov meets corn. In: Proc. 2005 Illinois Crop Protection Technology Conference, Urbana, IL, January 5-6, 2005.

Grift, T. E., Tekeste, M. Z., Raper, R. L., 2005a. Acoustic compaction layer detection. Transactions of the ASAE 48, 1-8.

Hachiya, M., Kagawa, T., Fujita, T., Kuwana, T., 1996. Study on the development of an autonomous cow-milking robot. In Proc. of the JSME Annual Conference on Robotics and Mechatronics (ROBOMEC '96). Japanese Society of Mechanical Engineering, Ube-City, Japan, June, 1996, pp. A: 596-597.

Han, S., Hendrickson, L. L., Ni, B., 2002. Comparison of satellite and aerial imagery for detecting leaf chlorophyll content in corn. Transaction of the ASAE 45, 1229–1236.

Han, S., Shin, B. S., Zhang, Q., 2003. Map-based control for autonomous tractors. Agricultural and Biosystems Engineering 4, 22-27.

Han, S., Zhang, Q., Ni, B., Reid, J. F., 2004. Guidance directrix approach for designing a vision-based vehicle guidance system. Computer and Electronics in Agriculture 43, 179-195.

Hannan, M. W., Burks, T. F., 2004. Current developments in automated citrus harvesting. ASAE Paper No. 04-3087, St. Joseph, MI.

Hebel, M., 2007. Meeting wide-area agricultural data acquisition and control challenges through Zigbee wireless network technology. ASAE Paper No. 701P0606, St. Joseph, MI.

Hofstee, J. W., Grift, T. E., Tian, L., 2004. Development of a tracking and guidance system for a field robot. AgEng Conference Paper. Leuven Belgium, September 12-16, 2004.

Hogewerf, P. H., Huijsmans, P. J. M., Ipema, A. H., Janssen, T., Rossing, W., 1992. Observations of automatic teat cup attachment in an automatic milking system. In: Proc. International Symposium on Prospects for Automatic Milking. Pudoc Scientific Publishers. Wageningen, Netherlands, November 23-25, 1992, pp. 80-90.

Hu, B. B., Nuss, M. C., 1995. Imaging with terahertz waves. Optical Letters 20, 1716-1719.

Humphreys, M., Ting, K. C., Roberts, W. J., 1994. Expert system for greenhouse glazing selection. In: Proc. 25th Congress of American Society of Plasticulture, Lexington, KY, pp. 52-58.

Jorgensen, R. N., Norremark, M., Sorensen, C. G., Andersen, N. A., 2008. Utilising scripting language for unmanned and automated guided vehicles operating within row crops. Computers and Electronics in Agriculture 62, 190-203.

Körner, O., Straten, G. V., 2008. Decision support for dynamic greenhouse climate control strategies. Computers and Electronics in Agriculture 60, 18-30.

Kawamura, N., Namikawa, K., Fujiura, T., Ura, M., 1984. Study on agricultural robot (Part 1). Journal of the JSAM 46, 353-358.

Kawase, K., Ogawa, Y., Watanabe, Y., Inoue, H., 2003. Non-destructive terahertz imaging of illicit drugs using spectral fingerprints. Optics Express 11, 2549-2554.

Kim, I., Kim, M. S., Chen, Y. R., Kondo, S. G., 2004. Detection of skin tumors on chicken carcasses using hyperspectral fluorescence imaging. Transactions of the ASAE 47, 1785-1792.

Kim, M. S., Chen, Y. R., Mehl, P. M., 2001. Hyperspectral reflectance and fluorescence imaging system for food quality and safety. Transactions of the ASAE 44, 721-729.

Kim, Y., Evans, R. G., Iversen, W., Pierce, F. J., 2006. Instrumentation and control for wireless sensor network for automated irrigation. ASAE Paper No. 061105, St. Joseph, MI.

Kim, Y. S., Reid, J. F., Hansen, A. C., Zhang, Q., 2000. On-field crop stress detection system using multi-spectral imaging sensor. Agricultural and Biosystems Engineering 1, 88-94.

Kise, M., Zhang, Q., Más, F. R., 2005a. A stereovision-based crop row detector for tractor automated guidance. Biosystems Engineering 90, 357-367.

Kise, M., Zhang, Q., Noguchi, N., 2005b. Obstacle detection using laser range finder for autonomous agricultural vehicles. Transactions of the ASAE 48(3), 1269-1278.

Kondo, N., 2003. Fruit grading robot. In: Proc. of IEEE/ASME International Conference on Advanced Intelligent Mechatronics, Kobe, Japan, July 20-24, 2003.

Kondo, N., K. C. Ting, E., 1998. Robotics for bioproduction systems. In: ASAE, (Ed.), St. Joseph, MI., pp. 325.

Kondo, N., Monta, M., 1997. Basic study in chrysanthemum cutting sticking robot. In: Proc. International Workshop on Robotics and Automated Machinery for Bioproductions. European Society of Agricultural Engineers, London, UK, September 1997, pp. preprint: 7-12.

Kondo, N., Monta, M., Fujiura, T., 1996a. Fruit harvesting robots in Japan. Advances in Space Research 18, 181-184.

Kondo, N., Ninomiya, K., Kamata, J., Chong, V. K., Monta, M., Ting, K. C., 2007a. Eggplant grading system including rotary tray assisted machine vision whole fruit inspection. Journal of the JSAM 69, 68-77.

Kondo, N., Ninomoya, K., Hayashi, S., Tomohiko, O., Kubota, K., 2005. A new challenge of robot for harvesting strawberry grown on table top culture. ASAE Paper No. 053138, St. Joseph, MI.

Kondo, N., Nishitsuji, Y., Ling, P. P., Ting, K. C., 1996b. Visual feedback guided robotic cherry tomato harvesting. Transactions of the ASAE 39, 2331-2338.

Kondo, N., Yamamoto, K., Taniwaki, S., Kuramoto, M., Kurita, M., Ninomiya, K., 2007b. Machine vision system for detecting rotten citrus fruit by use of UV LEDs. In: Proc. An International Conference on Biological Sensorics- Critical Technologies for Future Biosystems, Matsuyama, Ehime Japan, June 15-17, 2007, On database.

Kuipers, A., 1996. The milking robot. Agri-Holland 1-1996: 9-12 Department for Trade and Industry, Ministry of Agriculture, Nature Management and Fisheries, The Netherlands.

Lee, K. H., Ehsani., M. R., 2008. Comparison of two 2-D laser scanners for sensing object distances, shapes, and surface patterns. Computers and Electronics in Agriculture 60, 250-262.

Lejars, C., Gal, P. Y. L., Auzoux, S., 2008. A decision support approach for cane supply management within a sugar mill area. Computers and Electronics in Agriculture 60, 239-249.

Lu, R., Ariana, D., 2002. A near-infrared sensing technique for measuring internal quality of apple fruit. Applied Engineering in Agriculture 18, 585-590.

Malthus, T. J., Madeira, A. C., 1993. High resolution spectroradiometry: spectral reflectance of field bean leaves infested by Botrytis fabae. Remote Sensing of Environment 45, 107-116.

Matthews, K. B., Schwarz, G., Buchan, K., Rivington, M., Miller, D., 2008. Wither agricultural DSS? Computers and Electronics in Agriculture 61, 149-159.

Miller, B. K., Delwiche, M. J., 1991. Peach defect detection with machine vision. Transactions of ASAE 34, 2588-2597.

Mitsuhashi, T., Yamazaki, A., Shichishima, T., 1994. Automation of plant factory. In Proc. 4th SHITA symposium, Tokyo, Japan, pp. 45-57.

Morais, R., Fernandes, M. A., Matos, S. G., Serodio, C., Ferreira, P. J. S. G., Reis, M. J. C. S., 2008. A ZigBee multi-powered wireless acquisition device for remote sensing applications in precision viticulture. Computers and Electronics in Agriculture 62, 94-106.

Mueller, T. G., Hartsock, N. J., Stombaugh, T. S., Shearer, S. A., Cornelius, P. L., Barnhisel, R. I., 2003. Soil electrical conductivity map variability in limestone soils overlain by loess. Agronomy Journal 95, 496-507.

Nadimi, E. S., Søgaard, H. T., Bak, T., Oudshoorn, F. W., 2008. ZigBee-based wireless sensor networks for monitoring animal presence and pasture time in a strip of new grass. Computers and electronics in agriculture 61, 79-87.

Nara, S., Takahashi, S., 2006. Obstacle avoidance control for mobile robots based on vision. In: Proc. 2006 SICE-ICASE International Joint Conference, Pusan, South Korea, October 18-21, 2006, pp. 5335-5338.

Njoroge, J., Ninomiya, K., Kondo, N., Toita, H., 2002. Automated fruit grading system using image processing. In Proc. 2002 SICE Annual Conference, Osaka, Japan, August 5-7, 2002, pp. MP18-3(CD-ROM).

Noguchi, N., Will, J. D., Reid, J. F., Zhang, Q., 2004. Development of master-slave robot system for farm management. Computers and Electronics in Agriculture 44, 1-19.

Noh, H., Zhang, Q., Han, S., Shin, B., Reum, D., 2005. Dynamic calibration and image segmentation methods for multi-spectral imaging crop nitrogen deficiency sensors. Transactions of the ASAE 48, 393-401.

Patzoldt, W. L., Hager, A. G., McCormick, J. S., Tranel, P. J., 2006. A codon deletion confers resistance to herbicides inhibiting protoporphyrinogen oxidase. In: Proc. National Academy of Sciences 103 12329-12334.

Patzoldt, W. L., Hager, A. G., Tranel, P. J., 2005. A waterhemp (Amaranthus tuberculatus) biotype with multiple resistance across three herbicide sites of action. Weed Science 53, 30-36.

Reed, J. N., Miles, S. J., Butler, J., Baldwin, M., Noble, R., 2001. Automatic mushroom harvester development. Journal of Agricultural Engineering Research 78, 15-23.

Reid, J. F., Searcy, S. W., 1986. Detecting crop rows using the Hough transform. ASAE paper No. 86, 3042 St. Joseph, MI.

Reum, D., Zhang, Q., 2007. Wavelet based multi-spectral image analysis of maize leaf chlorophyll content. Computers and Electronics in Agriculture 56, 60-71.

Rossing, W., Hogewerf, P. H., 1997. State of the art of automatic milking systems. Computers and Electronics in Agriculture 17, 1-17.

Rovira Más, F., Zhang, Q., Reid, J. F., Will, J. D., 2004. Automated tractor navigation using stereo disparity images. Transactions of the ASAE 47, 1289–1300.

Saeedi, P., Lawrence, P. D., Lowe, D. G., 2006. Vision-based 3-D trajectory tracking for unknown environments. IEEE Transactions on Robotics 22, 119-136.

Sahin, E., Dallery, Y., Gershwin, S., 2002. Performance evaluation of a traceability system: an application to the radio frequency identification technology. In: Proceedings of the 2002 IEEE International Conference on Systems, Man and Cybernetics, Vol. 3, Yasmine Hammamet, Tunisia, October 6-9, 2002, pp. 647–650.

Sasaki, Y., Suzuki, M., 2003. Construction of the automatic diagnosis system of plant disease using genetic programming which paid its attention to variety. ASAE Paper No. 03-1049, St. Joseph, MI.

Shrestha, D. S., Steward, B. L., 2003. Automatic corn plant population measurement using machine vision. Transactions of the ASAE 46 559-565.

Simonton, W., Pease, J., 1990. Automatic plant feature identification on geranium cuttings using machine vision. Transactions of the ASAE 33, 2067-2073.

Slaughter, D. C., Giles, D. K., Downey, D., 2008. Autonomous robotic weed control systems: A review. Computers and Electronics in Agriculture 61, 63-78.

Snow, V. O., Lovatt, S. J., 2008. A general planner for agro-ecosystem models. Computers and Electronics in Agriculture 60, 201-211.

Song, H., Litchfield, J. B., 1990. Nondestructive measurement of transient moisture profiles in ear corn during drying using NMR imaging. Transactions of the ASAE 33, 1286-1290.

Subramanian, V., Burks, T. F., Arroyo, A. A., 2006. Development of machine vision and laser radar based autonomous vehicle guidance systems for citrus grove navigation. Computers and Electronics in Agriculture 53, 130-143.

Sugiura, R., Noguchi, N., Ishii, K., Terao, H., 2002. The development of remote sensing system using unmanned helicopter. In: Proc. Automation Technology for Off-Road Equipment, Chicago, IL, July 26-27,2002, pp. 120-128.

Sui, R., Wilkerson, J. B., Hart, W. E., Wilhelm, L. R., Howard, D. D., 2005. Multi−spectral sensor for detection of nitrogen status in cotton. Applied Engineering in Agriculture 21, 167-172.

Tang, L., Tian, L., Steward, B. L., 2000. Color image segmentation with genetic algorithm for in-field weed sensing. Transactions of the ASAE 43, 1019-1027.

Tang, L., Tian, L., Steward, B. L., 2003. Classification of broadleaf and grass weeds using Gabor wavelets and an artificial neural network. Transactions of the ASAE 46, 1247-1254.

Tanigaki, K., Fujiura, T., Akase, A., Imagawa, J., 2008. Cherry-harvesting robot. Computers and Electronics in Agriculture. 63, 65-72.

Tao, Y., Morrow, C. T., Heinemann, P. H., Sommer, J. H., 1990. Automated machine vision inspection of potatoes. ASAE Paper No. 90-3531, St. Joseph, MI.

Tian, L., 2002. Sensor-based precision chemical application systems. In: Proc. World Congress of Computers in Agriculture and Natural Resources, Iguacu Falls, Brazil, March 13-15, 2002, pp. 279-289.

Ting, K. C., 1997. Automation and systems analysis In: Plant Production in Closed Ecosystems, E. Goto, K. Kurata, M. Hayashi and S. Sase (Eds.), Kluwer Academic Publishers, pp. 171-187.

Ting, K. C., 2000. Automation-culture-environment oriented systems analysis (ACESYS) for controlled environment bio-production. Research for the Utilization of Insect Properties, National Institute of Sericultural and Entomological Science, Tsukuba, Japan, pp. 23-29.

Ting, K. C., Fleisher, D. H., Rodriguez, L. F., 2003. Concurrent science and engineering for phytomation systems. Journal of Agricultural Meteorology 59, 93-101.

Ting, K. C., Giacomelli, G. A., Shen, S. J., 1990a. Robot workcell for seedling transplanting part I - layout and materials flow. Transactions of the ASAE 33, 1005-1010.

Ting, K. C., Giacomelli, G. A., Shen, S. J., Kabala, W. P., 1990b. Robot workcell for seedling transplanting part II - end-effector development. Transactions of the ASAE 33, 1013-1017.

Ting, K. C., Sase, S., 2000. Object-oriented analysis for controlled environment agriculture. Environmentally Friendly High-tech Controlled Environment Agriculture, National Research Institute of Agricultural Engineering, Tsukuba, Japan, pp. 101-109.

Trevelyan, J. P., 1992. Robots for shearing sheep: Shear magic. Oxford University Press, London, UK.

Tung, C. P., Kak., A. C., 1996. Integrating sensing, task planning, and execution for robotic assembly. IEEE Transactions on Robotics and Automation 12, 187-201.

Van Henten, E. J., Hemming, J., Tuyl, B. A. J. V., Kornet, J. G., Bontsema, J., 2003. Collision-free motion planning for a cucumber picking robot. Biosystems Engineering 86, 135-144.

Van Henten, E. J., Hemming, J., Tuyl, B. A. J. V., Kornet, J. G., Meuleman, J., J., B., Os, E. A. v., 2002. An autonomous robot for harvesting cucumbers in greenhouses. Autonomous Robots 13, 241-258.

Van Straten, G., 2003. Field robot event, Wageningen, 5-6 June 2003. Computers and Electronics in Agriculture 42, 51-58.

Wang, N., Zhang, N., Wang, M., 2006. Wireless sensors in agriculture and food industry-Recent development and future perspective. Computers and Electronics in Agriculture 50, 1–14

Wang, Q., Zhang, Q., 2007. Stereo vision based trajectory tracking for agricultural vehicles. ASABE Paper 071016, St. Joseph, MI.

Wang, S. Y., Wang, P. C., Faust, M., 1988. Non-destructive detection of watercore in apple with nuclear magnetic resonance imaging. Scientia Horticulturae 35, 227-234.

Wang, X., Zhang, M., Zhu, J., Geng, S., 2008. Spectral prediction of Phytophthora infestans infection on tomatoes using artificial neural network (ANN). International Journal of Remote Sensing 29, 1693-1706.

West, J. S., Bravo, C., Oberti, R., Lemaire, D., Moshou, D., McCartney., H. A., 2003. The potential of optical canopy measurement for targeted control of field crop diseases. Annual Review of Phytopathology 41, 593-614.

Will, J. D., Noguchi, N., Reid, J. F., Zhang, Q., 2000. Sensor fusion framework for heading determination using GPS and inertial measurement. ASAE Paper 00-1070, St. Joseph, MI.

Wool Research and Development, 1988. Australian Wool Corporation. Shearing with robots. Highlights of the 1987-1988 Program, pp. 22-25.

Yang, C., Everitt, J. H., Bradford, J. M., 2004. Using high resolution QuickBird satellite imagery for cotton yield estimation. ASAE Paper No. 041119. St. Joseph, MI.

Yao, H., Tian, L., 2004. Practical methods for geometric distortion correction of aerial hyperspectral imagery. Applied Engineering in Agriculture 20, 367-375.

Zhang, Q., Ehsani, R., 2007. Telecommunications for data collection and dissemination. In: Ting, K.C., Fleisher D.H. and Rodriguez, L.F. (Eds.), Systems Analysis and Modeling in Food and Agriculture, in Encyclopedia of Life Support Systems (EOLSS) Eolss Publishers, Oxford ,UK.

Zhang, Q., Han, S., Reid, J. F., 2000. Agricultural infotronic systems for precision crop production. In: Proc. IFAC Bio-Robotics II, pp. 295-298, Osaka, Japan.

Zhang, Q., Qiu, H., 2004. A dynamic path search algorithm for tractor automatic navigation. Transactions of the ASAE 47, 639-646.

Zhang, Q., Reid, J. F., Noguchi, N., 1999. Automated guidance control for agricultural tractor using redundant sensors. SAE Technical Paper Series 1999-01-1874, p. 9. Warrendale.