

# Automation for Specialty Crops: A Comprehensive Strategy, Current Results, and Future Goals

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**Abstract:** Specialty crops are defined as fruits and vegetables, tree nuts, dried fruits and nursery crops including floriculture. In 2008 the US Department of Agriculture launched the Specialty Crop Research Initiative to promote innovative research and development in five legislatively-mandated areas: plant breeding and genetics; threats from pests and diseases; production efficiency, productivity, and profitability; innovations and new technologies; and methods to prevent, detect, monitor, control, and respond to food safety hazards. This article presents the technical goals and current progress of Comprehensive Automation for Specialty Crops, one of the 18 projects funded under the initiative in its first funding round.

**Keywords:** Specialty crops; Information, mobility, and manipulation; Plant science; Socio-economic analyses; Outreach.

## 1. INTRODUCTION

Specialty crops (fruits, vegetables, tree nuts, horticulture and floriculture) constitute a \$45 billion/year industry. As opposed to program crops (such as wheat, cotton, corn and soybean) they are characterized by the need for intensive cultivation.

While this industry is expected to grow steadily, it faces serious challenges today. Labor costs have increased significantly in the past decade. Not only is the cost of labor limiting economic returns, but also the seasonal availability and training requirements adversely affect the cost of production. Across the board, specialty crops are facing a crisis of increasing labor costs and shortages of available labor. In addition, an increasing consumer demand for a safe, affordable, traceable, and high quality food supply, and the need to minimize the environmental footprint represent key challenges for specialty crop sustainability in the United States.

Recently, our team started a four-year effort to develop a comprehensive automation strategy for tree fruit production (Baugher 2009). Our approach is based on a triad that spans the entire production spectrum, from the nursery tree stage to harvest (Figure 1):

1. Information, mobility, and manipulation technologies, including reconfigurable mobility, accurate positioning, information management and decision making, and augmented fruit harvesting.
2. Plant science technologies, including detection of plant stress and disease, monitoring of insect populations and infestation, automated caliper measurement, and autonomous crop load scouting.

3. Socio-economic analyses, outreach/extension, and commercialization.

In the paper we detail the objectives of and current progress achieved on areas #1 and #2, which comprise the technological core of the project. Our efforts on the socio-economic analyses and outreach, extension, and commercialization areas will be reported in companion papers in agricultural and economic journals.



**Figure 1. A pictorial representation of Comprehensive Automation for Specialty Crops (CASC). Needs originate from stakeholders who are also the recipients of the results in the form of outreach and commercialization activities.**

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## 2. INFORMATION, MOBILITY, AND MANIPULATION TECHNOLOGIES

The information, mobility, and manipulation technologies we are developing will provide the infrastructure for the deployment of sensors and tools that will enhance growers' understanding of their crops, foster better and quicker decision-making, reduce labor stress, and increase fruit quality. These technologies are described next.

### 2.1 Reconfigurable Mobility

We are creating low-cost, robust moving platforms that can be tasked flexibly based on specific needs of the growers. Several industry groups have identified the need for nimble, capable, and intelligent vehicles that can be flexibly tasked to perform various functions in orchards and nurseries (USDA 2007). Existing vehicles such as mobile harvesting platforms and tractors either have narrow functionality or are expensive enough to be used sparingly.

We intend to create autonomous vehicles in a way similar to personal computers – vehicles of various forms, sizes, and capabilities that enable users to switch form factors easily based on tasks and convenience. The core idea is to create the reconfigurable mobility needed for broad deployment across specialty crops.

Figure 2 presents the first in a line of vehicles we are developing. The Autonomous Prime Mover (APM) is based on a Toro Workman MDE electric vehicle. The APM will support the deployment of sensors such as Vision Robotics' Scout (see Section 3.5) and NTech's GreenSeeker (NTech 2009). In May 2009 the APM drove autonomously over 15 km of orchard rows, and in July 2009 is expected to drive over 100 km. In the future we will extend our automation to vehicles ranging from small tractors to larger agricultural platforms.

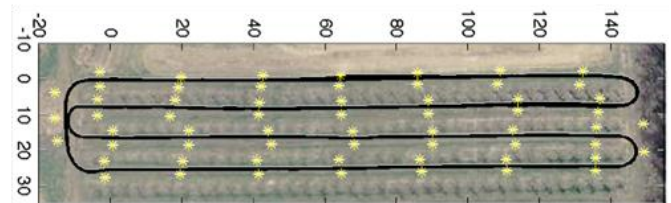


**Figure 2. The Autonomous Prime Mover, based on a Toro Workman MDE utility vehicle.**

### 2.2 Accurate Positioning

Accurate Positioning provides the capability of georeferencing specific observations even when GPS is unavailable. Existing solutions for high accuracy in these situations are prohibitively expensive. Our approach uses Bayesian estimation techniques for mobile robot localization and mapping (see, e.g., Thrun 2005).

To begin development of algorithms for accurate positioning in the absence of GPS we performed a data collection experiment in an orchard in Wexford, PA, in November 2008. The orchard was equipped with 24" traffic cones with a 4" retro-reflective collar, placed in pairs on either side of several rows, with pairs spaced approximately 20 m apart. An electric vehicle similar to the APM, instrumented with a nodding laser scanner, was manually driven around the rows. "Ground truth" measurements from a high-quality (approximately 2 cm) positioning system were collected along with time-stamped measurements from the scanner. Ground truth position and laser reflectivity data were used to create a map of the locations of the reflective cones. The resulting map was overlaid on a Google Maps aerial photo (Figure 3).

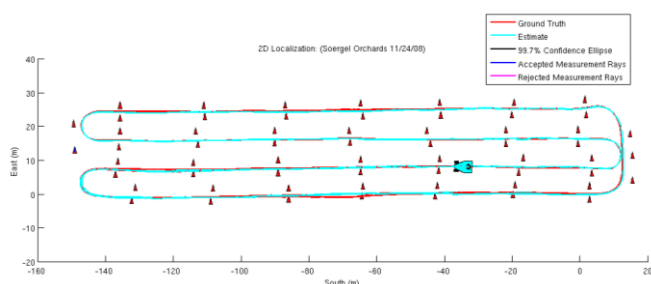


**Figure 3. Cone map overlaid on Google Maps aerial image. The black curve represents the vehicle trajectory during data collection, yellow stars represent cone positions. North is to the right.**

An extended Kalman filter (EKF) was constructed to produce an estimate of robot location given the map, laser data (i.e., range and bearing to a detected landmark), and robot odometry data (distance traveled, steering rate). Due to limitations of the computing architecture on the Workman, it was not possible to collect robot odometry. So virtual odometry measurements were generated from the ground truth signal, corrupted by a noise model with the following terms, where the values of the associated parameters were chosen to provide simulated performance comparable to that of currently available low-cost instrumentation:

- Gyroscope bias: This is a constant offset on the angular velocity measurement of the vehicle, causing dead-reckoned heading to drift over time. Here,  $B_g = 60$  deg/h.
- Odometry scale factor: This is a constant scale factor that multiplies the actual distance traveled to account for wheel slippage and uncertain tire size. Here,  $s = 0.98$ .
- Random noise: Stochastic effects on odometry are modeled by adding zero-mean, white Gaussian noise to the measured angular and forward velocities. This noise term is parameterized by the standard deviations in the angular ( $N_a$ ) and forward ( $N_f$ ) components. Here,  $N_a = 25$  cm/s and  $N_f = 15$  deg/min.

As shown in Figure 4, the resulting position estimate tracked the ground truth signal closely. A histogram of the errors observed over the course (not shown here for brevity) indicates that both the mean and median error were about 31 cm (where “error” is defined as the planar distance between the estimate and ground truth), and the  $3\sigma$  (99.7%) confidence interval was 1.0 m.



**Figure 4. Map of ground truth (red) and estimated (cyan) trajectories.**

In addition to addressing the problem of localization using a previously generated map, we are also investigating algorithms for simultaneous localization and mapping (SLAM). This approach has the advantage that it does not require a separate mapping step. We have obtained promising preliminary results for an EKF-based SLAM. In the future we will refine our SLAM algorithm and report on-line experimental results for both localization and SLAM.

### 2.3 Information Management and Decision Making

Information Management and Decision Making deals with the multi-scale, spatio-temporal data that must be integrated into a common geographic information system (GIS).

We are developing a GIS framework that integrates sensor data to generate spatial and temporal registered maps of indicators that support analysis and decision making required to achieve efficient production. Interaction with multiple sensors and actuators with disparate data bandwidth, frequency, density and latency requirements motivates careful consideration communication infrastructure. We will use a hybrid network that combines fixed and mobile sensors to deliver flexible data transport that meets coverage and cost goals. Our approach will provide broadband coverage to areas where high-bandwidth, low-latency communication is necessary, cover the remainder of the operation with a low-bandwidth, low-cost wireless network, and utilize mobile nodes fitted to APM vehicles to transport high-volume, high-latency stored data. Software will tie these layers together presenting a common interface to the GIS.

To date, two GIS display modes have been implemented that provide different ways to visualize time-varying sensor data. The first mode provides detailed access to an individual sensor’s measurement over time. The second mode supports comparative evaluation of spatial and time variation by animated coloring of the node location to reflect sensor data.

The two modes are currently being used to display data logs from previous sensor network orchard deployments.

The new GIS modes have been used to display data collected during a one-month deployment of a twelve-node sensor network at the Pennsylvania State University Fruit Research and Extension Center orchard, in Biglerville, PA. The data collected included node battery voltage, canopy temperature, and ground temperature, in addition to leaf wetness. Figure 5 shows an example of the second display mode being used to visualize leaf wetness data. Both modes are interactive and can be best experienced by loading files into Google Earth.



**Figure 5. GIS sensor network display mode for visualizing spatial data over time.**

### 2.4 Augmented Fruit Harvesting

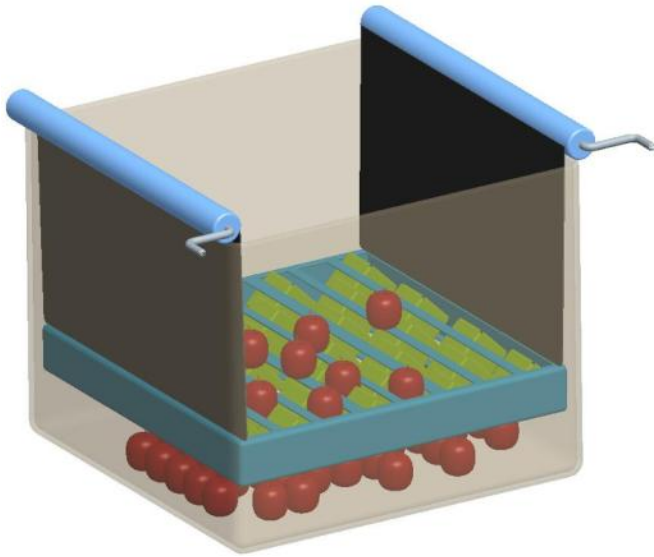
Augmented Fruit Harvesting focuses on increasing efficiency of fruit picking and reducing fruit damage in the field. The hand picking of fruit accounts for about 50% of total production costs, and a significant fraction of fruit (up to 30%) is damaged during harvest.

We will develop a variety of augmented/assisted harvest devices and tools, and field test them in actual orchards to validate each concept. They will cover the entire spectrum from fruit picking to transporting and bin filling. An example is shown in Figure 6.

There are very few commercial machines for fruit harvest against which we could benchmark our concepts. Therefore, we decided to compare our solutions with the traditional practice of harvesting fruit with a ladder and a bag.

At this stage in the project it is premature to quantitatively compare our ideas with existing alternatives. Instead, we determined eight evaluation criteria that we will use to qualitatively assess each design concept: cost, complexity, robustness, weight, ergonomics, ease of integration into current orchard operations, productivity, and potential for fruit damage. More details can be found in (Messner and Kliethermes 2009).





**Figure 6. Conceptual model of a granular absorption medium apple distributor design.**

### 3. PLANT SCIENCE TECHNOLOGIES

Biotic stress such as disease and insect damage account for 10-30% of yield losses while abiotic stress such as nutrient and water deficiency, temperature extremes, soil acidity, and excess water account for 70-90% of the yield reductions. Agricultural progress has primarily identified factors that limit productivity and provide either genetic improvement or cultural strategies to mitigate the stresses. We focus on technologies to detect plant stress and disease and crop load, as well as insect detection and monitoring, and integrate this information into management techniques that will increase productivity and quality of the final product. These technologies are described next.

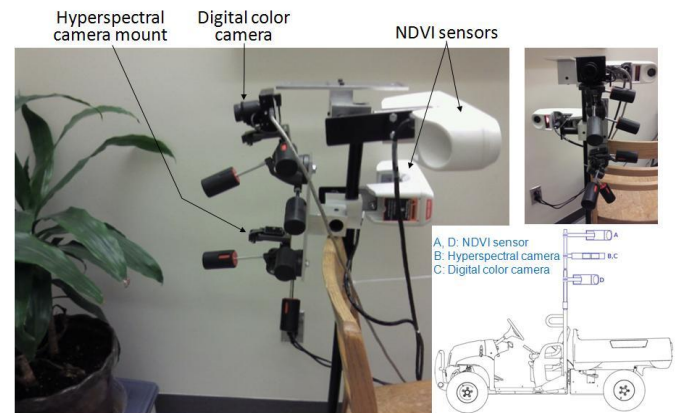
#### 3.1 Plant Stress and Disease Detection

Nutrient and water stress and disease significantly reduce plant productivity. Mapping methods using satellite or aerial images do not provide the level of accuracy and resolution adequate for detecting these problems at an early stage. In addition, while normalized difference vegetation index (NDVI) has been successfully used to detect plant stress in annual crops with 2D canopies (Moshou 2006), no reliable methods exist for mapping early stress development in complex 3D canopies such as orchard crops.

We are developing multi-modal sensor fusion algorithms to create accurate, high-resolution, three-dimensional maps of plant stress. We are also developing algorithms to identify early fire blight symptoms in the field using computer vision and machine learning (Freund 1997, Shyu 1999, Martinez 2001, Dy 2003). Data will be acquired by multiple NDVI sensors, multiple CCD cameras and a hyperspectral camera, all integrated and mounted on the APM.

Figure 7 presents our first prototype of a multi-modal data acquisition system. The mounting frame holds two NDVI sensors that are horizontally staggered to yield a vertical field-of-view and two tripod heads onto which a digital

camera and hyperspectral camera are mounted. A graphical user interface is used to capture, display, and analyze sensor data. Figure 8 presents the experimental greenhouse where we will execute initial tests before proceeding to full-scale testing at orchards in Pennsylvania and Washington.



**Figure 7. System components of a multi-modal data acquisition system.**



**Figure 8. Preparation of the greenhouse experiment with 48 apple trees for the study of water stress and fire blight disease detection.**

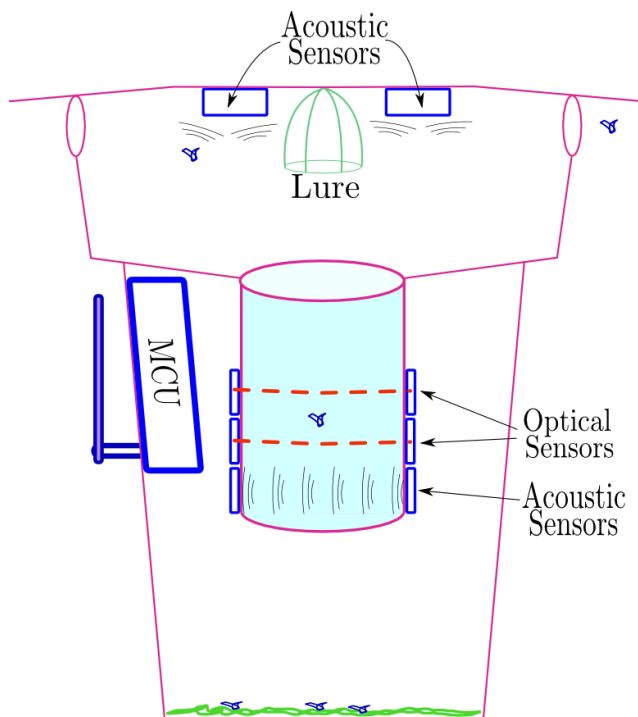
#### 3.2 Insect Population and Infestation Monitoring

Insect infestations reduce orchard productivity through tree death and reduced crop yield and quality; yet there is no system to auto-detect specific pest problems. There is a clear need for systems to monitor pest populations at high spatial and temporal resolution with little or no human intervention.

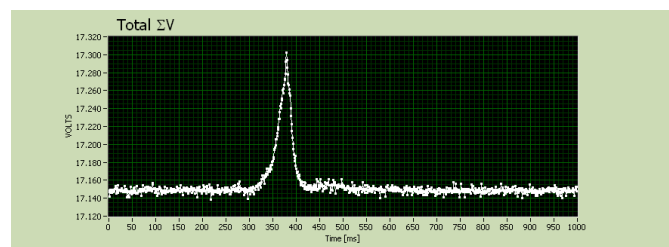
We are developing algorithms to identify codling moth and oriental fruit moth damage in the field using computer vision and machine learning (Freund 1997, Shyu 1999, Martinez 2001, Dy 2003). Codling moth (CM) and oriental fruit moth (OFM) were selected as models for automated detection because they are major problems in the tree fruit industry (Norelli 2003, Hull 2008), and damage symptoms are visually recognizable and can be integrated into a computer vision system. Likewise, we are developing automated sex pheromone trap sensor network systems for monitoring adult CM and OFM that can rapidly assess pest density levels and determine species.

We designed a prototype digital trap to count and identify insects on the field (Figure 9). At the trap entrance, near the pheromone lure, acoustic sensors record at different frequency levels the wing beats of the insects entering the trap. Once the insects enter the trap, they are killed immediately by the insecticide and fall to the bottom. As they fall through the tunnel, the insects are detected using several inexpensive sensors. We are currently experimenting with a sensor suite composed of optical and acoustic sensors. Optical sensors are better at detecting small insects inside the tunnel, but are susceptible to varying external lighting conditions. An ultrasound receiver/transmitter pair, on the other hand, is insensitive to light, but is likely to produce false positives during strong shaking of the trap (e.g., by wind).

We tested whether the prototype digital trap can count free-falling insects using adult OFM. Figure 10 shows the output signal when an OFM adult is dropped into the trap. The voltage peak clearly allows for insect detection.



**Figure 9. Schematic design of the digital trap.**



**Figure 10. Output signal response when an OFM adult falls through the tunnel in the digital trap.**

We also developed a prototype algorithm for detecting the evidence of damage by internal feeding moths (IFM) within apples. The algorithm assumes that individual apples have been extracted from an image. Given a segmented apple image, the algorithm classifies whether or not the apple has

IFM damage. The algorithm consists of four main steps: color-based segmentation, contour extraction, detection of candidate regions of IFM damage, and classification of candidate regions. Preliminary quantitative results using 98 IFM-damaged apples and 491 healthy apples are as follows:

Correctly detected IFM-damaged apples	91.8%
Healthy apples falsely detected	13.2%

Figure 11 shows two examples of regions on the fruit correctly and incorrectly classified as IFM-damaged. On lighter-colored fruit (yellow or green apples), the damage is visually conspicuous, but on dark red apples such as “Red Delicious” damage symptoms are more difficult to detect. Natural features of the apples such as the calyx may also appear superficially similar to damage, and cause the false negatives.



**Figure 11. Examples of regions on the fruit correctly (on the left) and incorrectly (on the right) classified as IFM-damaged.**

### 3.3 Automated Caliper Measurement

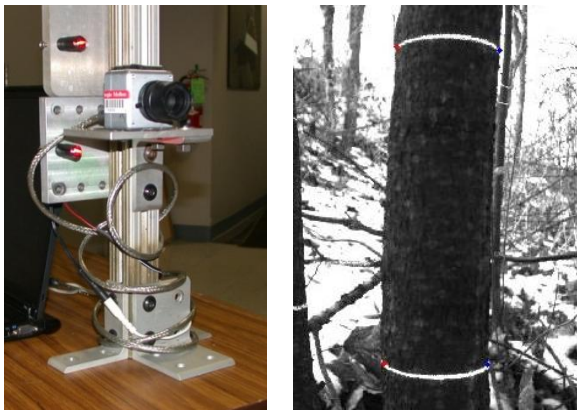
Caliper, a measure of growth and marketability, is manually measured in tree crops, consuming time from a diminishing labor pool of low-skilled workers. Currently, measuring caliper (and counting trees) is a costly process in which data are not spatially or temporally recorded; instead the information is hand-logged revealing no or little information about management practices and current/future inventory.

We are developing systems and algorithms to automate caliper measurement and tree count. An initial laboratory prototype using two laser planes and a camera is shown in Figure 12 (left). Its purpose is to generate data that we are using to validate the automatic measurement software. Figure 12 (right) shows a typical result, where the diameters of two trees are determined by counting the pixels within the trunk, taking into account perspective effects. A more robust, fieldable system is currently under construction and will soon be deployed at a large-scale nursery in Oregon.

### 3.4 Autonomous Crop Load Scouting

Current methods of crop load estimation have errors in excess of 25%, decreasing the ability to make effective production management decisions, plan and match harvest with orders, and control inputs such as fertilizer, irrigation, and pest control measures.





**Figure 12. (Left) Prototype automated caliper measurement system. (Right) The system estimates tree diameter by processing images captured by the camera.**

We are developing a crop load estimation system for medium- to high-density orchards. The Scout scans fruit trees to determine the total crop yield, and the size, location, and color of each piece of fruit in the orchard. The existing prototype was sufficient to demonstrate a proof-of-concept. Going forward, the goal is to create a production Scout with both robust software and hardware.

The current design is the first full prototype, which is defined as including the form and function of the anticipated design while still requiring more evolution to reach the production design. Our goal is to create a system that accurately detects more than 95% of the fruit in a typical orchard.

To date, we have demonstrated the ability to continuously scan trees and collect data with sufficient detail and clarity for visual analysis. The software infrastructure is in place to detect apples of all colors. Basic boosting algorithms address the color issue – e.g., to discern green fruit from other green objects such as leaves and grass. In real-world conditions, lighting, shadows, shape coincidences, and occlusions (due to leaves, stems, branches, tree trunks, and even other apples) greatly affect performance. Figure 13 shows an example of red apple detection.



**Figure 13. Red apple detection using the Scout crop load estimation system.**

## DISCUSSION

CASC is a four-year project aimed at developing a comprehensive automation strategy for specialty crops, with

an initial focus on apples and nursery trees. While our preliminary Year 1 results show that it is possible to develop technologies to increase farm efficiency, reduce labor costs, and increase fruit quality, our (and others') greatest challenges will be to prove these technologies' economic feasibility and overcome any barriers to adoption. These are being addressed by our team in efforts parallel to those reported here and will be the subject of future articles.

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