Current Developments in Automated Citrus Harvesting

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Abstract. The area of intelligent automated citrus harvesting has become a renewed area of research in recent years. The renewed interest is a result of increased economic demand for better solutions for selective automated citrus harvesting than are currently available by purely mechanical harvesters. Throughout this paper the main challenges facing intelligent automated citrus harvesting are addressed: fruit detection and robotic harvesting. The area of fruit detection is discussed, and incorporates the important properties of citrus that can be used for detection. Robotic harvesting is covered, and involves the discussion of the main mechanical design needs as well as the use of visual servoing for the control of the robotic harvester. A description of our proposed intelligent citrus harvesting system as well as our current prototype is presented.

Keywords. Harvesting, harvester, picking, fruit, citrus, oranges, image processing, machine vision, real time, automated, mechanical, visual servoing, gripper, robot, robotic
Introduction

Strictly mechanical harvesting systems that are currently being operated work on the idea of shaking or knocking the fruit out of the tree. The two basic designs are the canopy shaker and the trunk shaker. The trunk shaker based systems attempt to remove the fruit from the tree by simply shaking or vibrating the trunk of the tree and allowing the induced vibrations and oscillations to cause the fruit to fall out of the tree. Canopy shaker systems, see figure 1, typically use larger rotating drums with protruding "fingers" that are inserted into the tree's canopy. The rotating fingers allow for better shaking of the canopy than the trunk shakers alone.

![Canopy Shaker Design for Mechanical Citrus Harvester](image)

However, the main problem with these strictly mechanical harvesters is that citrus typically have a strong attachment between the tree branch and the fruit. Thus it may require a large amount of shaking before the fruit can be harvested which can cause several problems. The first is that the shaker system may cause physical damage to the tree, such as bark removal and broken branches. Second, and most importantly, the fruit has a high probability of being damaged by either the shaker system or falling out of the tree, and thus mechanical shakers systems are typically only used for juice quality fruit. Though fruit used for the making of juice is a large part of the citrus market there is still a large percentage of citrus that is sold as fresh market fruit, which cannot be damaged in any way. Due to these problems a better and more intelligent citrus harvesting system is needed.

Earlier attempts in the 1980's and early 1990's showed promising research efforts in creating viable automated "intelligent" citrus harvesting systems. The focus of most research efforts has been to design a harvesting system that can replicate the precision of a human harvester while achieving the efficiency and decreased labor of the purely mechanical harvesters. The basic design used for an intelligent automated citrus harvesting system typically consists of a vision system for the detection of fruit and a robotic manipulator for the harvesting of the fruit. The difficulty of this approach involve the natural complexity of the harvesting environment, which requires sophisticated vision algorithms to help discern the fruit from the branches and leaves of the tree under varying weather and lighting conditions. The robotic manipulator must be able to remove the fruit as quickly as possible with out damage to the fruit or the tree despite the fruit's location relative to the tree's canopy.

Due to the limitation in technology and monetary funding no single harvesting system was designed that could provide a sufficient harvesting efficiency to make the system economically

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feasible. The most promising efforts were made through the French and Spanish EUREKA project named CITRUS, which was initiated in 1988, IVIA (2004). The project involved both French and Spanish research and development institutions and companies. The project was able to demonstrate satisfactory operation by 1997. The system achieved harvest rates up to 80% for fruit on specially adapted trees, but could only manage 60-65% harvesting rate on standard trees. The project was suspended in 1997 due to several factors, including the inability to fully adapt the system to commercial groves, excessive system costs, and lack of funding.

In this paper the most important problems in designing an intelligent automated citrus harvester will be presented. We cover in detail the problems of fruit detection using machine vision, the design of the robotic system, and finally how the vision and the robotic system need to be coupled in order to provide the needed robustness and precision to make an automated harvester economically feasible.

**Fruit Detection**

One of the most important components of an intelligent automated citrus harvesting system is the detection of the fruit. The robotic system can only harvest the fruit that has been detected, and thus it is vitally important that the fruit detection system be both accurate and robust. Many different properties can be used to detect citrus from its natural environment, but a successful detection strategy will need to use several different properties depending on the harvesting situation.

**Color**

The most obvious property of citrus is its color. Many different researchers such as Parrish (1977), Tutle (1983), Sites (1985), Rabatel (1988), Harrell (1989, 1990, 1990), Grasso (1996), Levi (1988), Weeks (1999), Plebe (2001), and Bulanov (2001) have used color-based vision for their research efforts. The toughest obstacle faced when looking for a certain color is the variations in color due to many different factors. Oranges, for example, may be less ripe and take on a more yellowish color rather than the typical "orange" color, and others may have been affected by weather or disease and may take on more of a brownish color. Therefore, the color detection algorithm must be able to detect these different shades of color.

Another problem that can arise with color detection is lighting. Without the proper lighting the color of the fruit can vary greatly. The main contributing factor to lighting of a harvesting scene is sunlight. The amount of sunlight that is available as a result of cloud cover and the sun’s angle with the harvesting scene can cause significant variances in how the harvesting scene appears. Figure 2 shows the same scene under two different sunlight conditions. Figure 2 (a) is the result of indirect sunlight, as may be experienced on a cloudy day. The resulting image captured by the camera is very uniform in brightness across the entire image, and provides consistent coloring of the leaves and fruit. Figure 2 (b) is the result of direct sunlight on the harvesting scene. The direct sunlight causes a drastic change in brightness across the scene, and both the leaves and fruit can take on very different shades or hues of color.
Figure 2. Lighting Problems: a) Indirect Sunlight and b) Direct Sunlight

Figure 3 shows the general effects of poor lighting. Figure 3 (a) shows the results of a scene in which the lighting has caused significant shadows. As with the direct sunlight image from figure 2 (b), the differences in color can vary greatly, and the lack of light in the shadows causes the color of the fruit to become dark or colorless. Figure 3 (b) shows the results of insufficient lighting. Without enough light the color appears washed out of the scene, and it is difficult to discern the difference between the fruit and the leaves.

Figure 3. Poor Lighting: a) Shadows and b) Insufficient Lighting

Color alone cannot provide a sufficiently robust algorithm for the detection of citrus. The most significant problem is the detection of objects that appear the proper color, but are not fruit. There can be any number of reasons for false detections such as image noise, man-made objects, reflections, etc. Therefore a robust detection strategy will need to incorporate other properties of the citrus than just color.

Shape

The other obvious property of citrus is its shape. Many different researchers such as Whittaker (1987), Pla (1993), Grasso (1996), Levi (1988), Weeks (1999), and Plebe (2001) have incorporated shape into their fruit detection algorithms. Citrus in general tends to have a round shape, where as tree branches and leaves tend to have more straight or pointed shapes. Looking for round objects can be a simple way to detect fruit, but as with color detection, shape detection can also have several problems. The main problem is occlusion. Figure 4 shows images of the two main types of occlusion when observing oranges. Figure 4 (a) is an example of leaf occlusion. Leaf occlusion complicates fruit detection by disrupting the shape of the fruit and minimizing the amount of the fruit's color that is visible. Figure 4 (b) is an example of fruit occlusion caused by the clustering of several fruit. Fruit occlusion also disrupts the shape of the fruit in much the same way as leaf occlusion. Fruit occlusion can cause multiple fruit to appear
as a single larger fruit, unlike leaf occlusion where there is distinct contrast in color between the leaf and the fruit.

![Fruit Images](image)

Figure 4. Occlusion Problems: a) Leaf and b) Fruit Clustering

Another situation that is important is that there are certain varieties of orange trees that grow both the current season’s harvestable fruit as well as next year’s immature fruit. The result is that the tree will have both orange and green colored oranges at the same time.

A successful citrus detection strategy will require the understanding and full exploitation of both the color and shape of the fruit. Image processing will be needed to determine how to best detect the color in a variety of lighting conditions, while at the same time being able to compensate for the differences in the fruit’s natural color. Image processing will also need to detect fruit when leaves or branches occlude it, or when it is clustered with other fruit. A fruit detection algorithm that is economically feasible for mass harvesting will require a combination of both the color and shape properties of citrus.

**Fruit Removal**

Once the fruit has been detected, it is up to the robotic system to actually remove the fruit from the tree. The system not only requires a well-designed robotic harvester, but also requires efficient integration of the robotic harvester with the fruit detection system.

**Robotic Harvester**

Following the research of many previous researchers, such as Ceres (1998), D’Esnon (1985, 1987), Harrell (1990, 1990), and Kassay (1992, 1993), the common solution to an intelligent robotic harvesting system is the use of a robotic manipulator/arm. The robotic system of the French Spanish EUREKA CITRUS project can be seen in figure 5.

![Robotic System](image)

Figure 5. Robotic System Used in the EUREKA Project
The easiest and most common solution is to design a three degree-of-freedom (DOF) robotic manipulator/arm. The three DOF arm is the simplest design that can harvest an individual fruit given that its relative location to the robot is known. The fruit detection algorithm is used to supply the fruit’s three-dimensional position (i.e. x, y, and z). The position coordinates from the fruit detection system are used by the robot’s controller to calculate the three joint positions of the robot needed to reach the desired position. The biggest drawback of using a three DOF design is that the robot is only able to reach the desired position, and due to its lack of degrees of freedom has no ability to adjust the orientation of the gripper used for grasping the fruit. This is a noticeable problem when a fruit is located behind an obstacle such as a branch. Without the ability to adjust the gripper’s orientation, the gripper may not be able to properly grasp the fruit. This means that the fruit is either not mechanically harvested, or that time must be wasted to try to harvest the fruit later when the robot is in a more desirable position.

The use of a five or six DOF manipulator can remedy this problem by allowing for the ability to adjust the orientation of the gripper. In addition to position, a five DOF arm can provide both pitch and yaw. A six DOF arm can also provide the motion of roll. However, even with enough DOF to provide both position and orientation, the more extreme case of a fruit located in the interior of the tree can still be a problem. In this case there may be several obstacles between the robot and the desired fruit. Even if the robot has the ability to adjust for orientation, the problem with a basic five or six DOF robot is that there are only two different arm poses that allow for the desired position and orientation. The two poses/configurations are often referred to as elbow up and elbow down, and is a direct result of mathematics and kinematics. The problem exists when the robot reaches into the tree causing the pose of the robot to collide with the tree. Depending on the situation this may cause damage to the fruit, the tree, or possibly the robot.

A better solution is to use a robotic manipulator that has at least one more DOF than is needed for the positioning and orientation task. These types of robotic manipulators are referred to as redundant manipulators. A redundant arm can provide not only position and orientation, but it can also provide an infinite number of poses for the desired position and orientation. This allows for adjusting the robot’s pose “on the fly,” as to avoid collisions or to place the arm in a more efficient pose for harvesting.

Along with the robotic manipulator, the other main mechanical design problem involves the gripper used for grasping the fruit. The basic need of the gripper is to grasp or attach to the fruit so that it can be removed. The two basic designs are a hand-based gripper and suction cup based gripper. The hand-based gripper uses fingers, much like that of a human hand, to physically grasp the fruit. The fruit is maintained in the gripper’s fingers by applying positive pressure to the fruit. The suction cup based gripper uses one larger or several smaller suction cups to attach to the fruit. The idea is to use the negative pressure provided by the vacuum in the suction cups to hold the fruit. In both design setups, too much positive or negative pressure can cause damage to the fruit, and not enough pressure can cause the fruit to be dropped during removal.

Visual Servoing

The most critical part of a vision-based robotic fruit harvester is the interaction of the fruit detection algorithm with the robotic harvester. The concept is to use the information about the detected fruit derived from the vision system and transform it into commands that can be used to direct the robotic system to the desired location and perform the desired actions. This is often referred to as visual servoing.
The two dimensional camera image information \((x_c, y_c)\) that contains the locations of the fruit must be transformed into a three dimensional position \((x, y, z)\) information that locates the fruit in the physical environment. An example of the detected fruit locations in an image can be seen in figure 6.

![Example Image After Fruit Detection](image)

Figure 6. Example Image After Fruit Detection

The range or distance from the camera to the image scene is the missing information. If the range \((z)\) is known for a specific pixel in the image, then the corresponding \(x\) and \(y\) positions can be found via

\[
\begin{bmatrix}
x_c \\
y_c
\end{bmatrix} = \begin{bmatrix}
x/z \\
y/z
\end{bmatrix}.
\]

(1)

It is important to note that every pixel location in the image can have a different range associated with it, and thus the exact spatial position depends on how accurately the range can be determined. Poor accuracy in the range to a desired point will give poor \(x\) and \(y\) location information. The range information used for equation 1 can be obtained in many ways, but there are three basic methods. The first and most common method is to use a range sensor like an ultrasonic sensor or a photoelectric sensor. These sensors can typically only return a single distance reading to a single point or region. That is, they cannot provide the exact range for all the pixels in the image, but they can, at best, give the exact distance to a specified point that can be used as an average distance to the scene. The resulting 3D coordinates will not be exact for the entire scene, but typically this setup can provide a good estimate. The second way is via stereo imaging. The use of a stereo pair of cameras can also be used in much the same way to get the average range to the image scene. The use of stereo imaging does not require the use of a range sensor since the range information is determined via the stereo image processing algorithm, but at the cost of increased complexity and the need for more computation time. The third and most accurate method to determine the range to the entire image scene is to use a scanning sensor, such as offered by SICK, Inc. These sensors typically use a laser range sensor that can be repositioned. The laser basically scans from side to side to provide 2D range data. The 2D scanning system can then be scanned up and down to provide a 3D image of range data. Though these systems can provide more accurate results for equation 1, they are both bulky and slow, and thus they do not readily provide for realistic use in a citrus harvesting system.

Once the detected fruit locations are transformed from the image to the spatial environment, the next step is to use these 3D values to servo the robot. There are two different means that this 3D information can be used to servo the robot. The first is via open loop control in which the 3D coordinates are provided to the robot's controller, and are used to servo to the exact location without any further interaction with the fruit detection algorithm. This yields the easiest and simplest way to servo the robot, but it is also the least robust. The problem that affects this
scheme is that the fruit's physical position is constantly changing in time due to many factors such as wind, vibrations and oscillations in the tree canopy caused by the removal of other fruit, or the unloading of fruit weight from the tree branches. If a fruit is detected at a given location at a given time, then it is very possible that by the time the robot is positioned to the predetermined position the fruit may no longer be in the same position. Also, the fruit's detected location is only as accurate as equation 1 allows. Any error in the range to the desired fruit will cause errors in the x and y position. Either of these cases would mean that the fruit could not be properly harvested.

The solution to the open loop problems is to use feedback control. In this scheme the location of the desired fruit is constantly updated to provide the most accurate coordinates for servoing of the robot. Though this idea can provide a much more robust harvesting algorithm, it is much more complicated than the open loop algorithm. There are two major problems that need to be addressed when using feedback control for visual servoing. The first is that of tracking the desired fruit. Though this idea seems simple it is important to note that the camera simply takes successive "still" images to capture motion. Therefore in order to track an object that is moving an algorithm must be designed to find the same object in the different "still" images. Typical tracking algorithms use the relative displacement of located objects within the successive image, while others use properties, such as shape and size of the objects, to determine which objects in each frame are the same object in another frame. Without an accurate and robust tracking algorithm it is not possible to use feedback control in visual servoing.

The other important problem is servo update time. To design a robust and efficient feedback visual servo system requires that the fruit’s position is updated as often as possible. The lower the update rate, the less reactive the system will be to changes in both the fruit’s and robot’s position. It will also be more sensitive to the accuracy of equation 1, since the more often the fruit’s position is updated the more often that the range information can be determined and corrected for.

The rate at which the tracking algorithm can be updated is very dependent on the speed of the image processing algorithms. A complex image processing algorithm can take tens to hundreds or more milliseconds to complete. Thus, update rates can easily be slowed to as low as one to ten times a second even on the fastest and most current computer systems. In comparison, a standard NTSC video camera has a rate of about 30 images per second. The faster the harvesting system is needed to work the faster the update rate that is needed. For a given harvesting cycle speed experimental results have shown that an average update rate of ten times a second is needed for adequate harvesting system control, but rates of twenty or thirty times a second yield much better results both in terms of harvesting system responsiveness and robustness. The image processing algorithms for fruit detection must be designed and implemented to provide not only accurate results, but also to minimize computation time to the order of tens of milliseconds to be able to provide a feasible robotic harvesting system.

Conclusion

The design of an intelligent automated citrus harvester should be composed of three main systems. The first system is for the detection of the fruit, and should be based on color vision. The supporting image processing algorithms should be able to detect fruit by color under a variety of lighting conditions, distinguish citrus by its shape, and do so with processing times on the order of tens of milliseconds. The second system is the robotic harvester. The use of a redundant robotic manipulator can provide the ability to intelligently and precisely select which of the fruit should be harvested, and allow for much greater dexterity in removing the fruit then is possible by traditional mechanical harvesters. The redundancy of the manipulator allows for
increased maneuverability that can be an added benefit in the complex harvesting environment of citrus trees. The final system is the visual servo system that incorporates the fruit detection algorithm with the ability of the robotic harvester. A closed loop feedback system that constantly updates the position of the fruit over time can provide more accurate and robust harvesting of the fruit. This model for an intelligent citrus harvester system will be able to replicate the precision of a human harvester, thus providing selective harvesting potential.

**Future Research**

Our current research effort is focusing on evaluating the proposed problems with a prototype harvesting system. The machine vision system is based on a Sony FCB-EX780S “block” camera that is commonly used in commercial “camcorders.” The camera has analog video output that is standard NTSC with s-video signal output, and is classified as high resolution with 470 TV lines. The camera is located on the end-effector of the robot in the harvesting environment. The analog signal from the camera is directed to a FlashBus MV Pro frame grabber for conversion to a digital 640x480 RGB bitmap image. The robotics system consists of a Robotics Research model 1207 seven DOF manipulator and controller. It has a maximum end-effector velocity of 20 inches per second and a maximum payload capacity of approximately 20 pounds. The end-effector is a Schunk, Inc. pneumatic hand-based actuator with custom designed fingers. A pair of ultrasonic sensors is integrated into the end-effector, and is used for range information. The image processing and visual servoing systems are both performed on a single 2.8 GHz Pentium 4 equipped Advantech PCA-6186 CPU card. The combined computation time of both the image processing and visual servoing varies from 15 ms to a maximum of approximately 80 ms. The current prototype version of our robotic harvesting system can be seen in Figure 7. The results of our research prototype will be documented in upcoming publications. We are also researching other prototype systems for robotic harvesting with an emphasis on manipulator and gripper design.

![Figure 7. Current Prototype Intelligent Citrus Harvesting System at the University of Florida](image)

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**References**


