An Image Processing Approach to Distance Estimation for Automated Strawberry Harvesting

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Abstract. In order to successfuly navigate between rows of plants, automated strawberry harvesters require a robust and accurate method of measuring the distance between the harvester and the strawberry bed. A diffracted red laser is used to project a straight horizontal line onto the bed, and is viewed by a video camera positioned at an angle to the laser. Using filtering techniques and the Hough transform, the distance to the bed can be calculated accurately at many points simultaneously, allowing the harverster's navigation system to determine both its position and angle relative to the bed. Testing has shown that this low-cost solution provides near-perfect field performance.

Keywords: automated harvesing, distance estimation, Hough transform.

1 Introduction

Within the strawberry industry, labour costs have always represented by far the highest proportion of expenditures. Additionally, high competition for the limited labour supply in the horticultural industry has meant that the availability of seasonal workers such as pickers and packers is often inadequate during times of peak output, leading to decreased yeild and significant waste [3]. The continual increase of labour costs and the steadily reducing labour pool has seen strawberry producers look towards technological solutions such as automated harvesting, packing, and grading of fruit.

Automated harversting of strawberries presents a number of unique difficulties. Strawberries are extremely fragile fruit, and easily damaged. In addition, damaged fruit commands a significantly lower price than undamaged fruit, and is usually sold at a net loss for jam and other such secondary uses. Even seemingly minor blemishes on the fruit can significantly reduce the final sale price. For this reason, any automated harvesting must be done in a very precise and gentle manner. If possible, the fruit itself should never be touched, but rather moved only by means of the peduncle (stem) of the fruit, which is significantly more difficult to find than the fruit itself.

M. Kamel and A. Campilho (Eds.): ICIAR 2011, Part II, LNCS 6754, pp. 389–396, 2011.

Strawberries must also be picked at the right time, as they do not ripen significantly once removed from the plant. If picked too early, the unripe fruit are unsuitable for sale. If picked too late, the fruit will likely be rotten, meaning that not only will that particular piece of fruit be lost, but a much higher chance of fungus and other diseases for neighbouring plants. For these reasons, human pickers are trained to pick all ripe fruit, and any automated system must match this level of accuracy to be acceptable. Foilage presents yet another difficulty in this regard, as much of the fruit is hidden under leaves which must be moved before picking can commence.

Finally, the harvester must be able to quickly and accurately move along the rows of plants, stopping precisely in front of each to harvest. In the uneven, muddy terrain of an outdoor strawberry field, this can present difficulties. Although generally straight, many fields have local curvature, and as such the harvester must be capable of accurately traversing such curves in order to keep the picking head within reach of the fruit, and avoid causing damage to the plants themselves.

It is this latter problem which is addressed in this paper. As shown in figure 1, strawberries are typically grown on raised beds, with a valley running between adjacent beds. This provides both a natural path for the harvester to travel along, and a convenient point of reference for measuring the distance to the plants. By measuring the distance to the bed at both the front and rear of the harvester, both an average distance and angle can be calculated. As the harvester completely straddles the bed, this can be done on both sides simultaneously allowing for greater accuracy.

Distance measurement can be performed in a number of ways. Ultrasonic distance measurement, which function by detecting echoes from a high-frequency sound wave, are quite accurate over small distances, and relatively cheap [5]. Unfortunately these devices only work well for detecting hard surfaces such as metal, glass or wood, and perform poorly in the conditions experienced in a typical strawberry field. Preliminary testing showed that accuracy was unacceptably low for this application.

Another popular method of distance estimation is laser range finding. These systems typically operate by measuring either the time taken for a pulse of coherent light to travel to an object and return, or by measuring the phase shift in the returned light. Although these technologies are very accurate, their size and cost makes them unsuitable for the harvester application.

Image processing techniques also provide a solution to this problem. By shining a line of coherent light onto the bed, and viewing this line with a video camera at an angle, an accurate and robust distance measure can be calculated. As the harvester already contains a number of video cameras, this solution involves only the addition of a single laser source, which is extremely cheap. The physical layout of the system is described in section 2, and the processing used to determine the distance explained in section 3. Experimental results of the proposed technique from both laboratory and field testing are provided in 4.

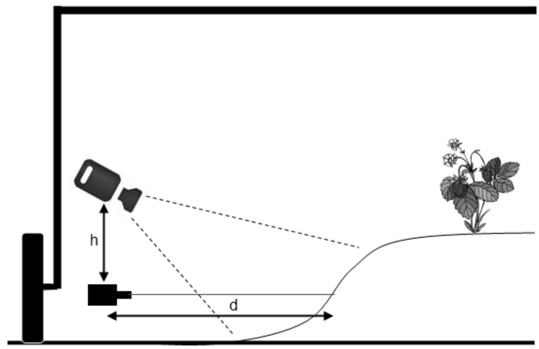

Fig. 1. Layout of strawberry beds, showing position of harvester, laser, and camera

2 Harvester Environment and Camera Setup

The automated strawberry harverter consists of an outer shell, completely enclosed to prevent any natural light from entering, with all robotics and control systems contained internally. As shown in figure 1, the harvester straddles the bed, with plastic and rubber sheeting allowing it to pass smoothly over the plants without letting significant amounts of light in. By avoiding natural light, the illumination of objects of interest can be more accurately controlled, thus enabling simpler processing.

The laser used to illuminate the bed has a wavelength of 650nm, with a nominal power output of 5W. It is mounted on the side panel of the harvester, and a level which corresponds to roughly half the height of the bed. This can be easily adjusted for use in fields which have variable bed heights. In order to create the horinzontal line, a diffraction grating is placed immediately in front of the laser. Strawberry beds are generally covered entirely in plastic sheeting to prevent weeds. This sheeting allows excellent reflection of the laser.

The camera used to detect the image is a Tucsen TCA 1.31C, with a Micron MT9M131 $\frac{1}{3}$" CMOS sensor, and is mounted directly above the laser, with a separation distance of 0.21m. During testing the camera was angled downward at 41°, as this angle gave the best possible view of the bed. This angle can be modified for situations where the bed is significantly narrower or wider. The camera outputs uncompressed frames at 25fps, at a resolution of 640x480. A physical colour filter matched to the wavelength of the laser was attached to the camera to remove any unwanted signals.

3 Processing Algorithms

3.1 Pre-processing

In order to speed up processing, frames are downsampled to 160x120 pixels. This resolution was found to be sufficient for high accuracy, and allows a much higher number of frames to be processed per second and thus greater control of the harvester. An example of such an image is shown in figure 2(a). Correction for lens distortion was then applied, in order to obtain a true representation of the image plane. This operation is carried out automatically in software using data obtained with a special calibration image. Following this, the red channel is extracted, and it alone used for further processing. The result of this is shown in figure 2(b). Lens distortion correction provides a muich straighter laser line, whilst extracting the red channel greatly increases the brightness of the line compared to the rest of the image. These operations significantly improve the results of the Hough transform, and the overall accuracy of the system.

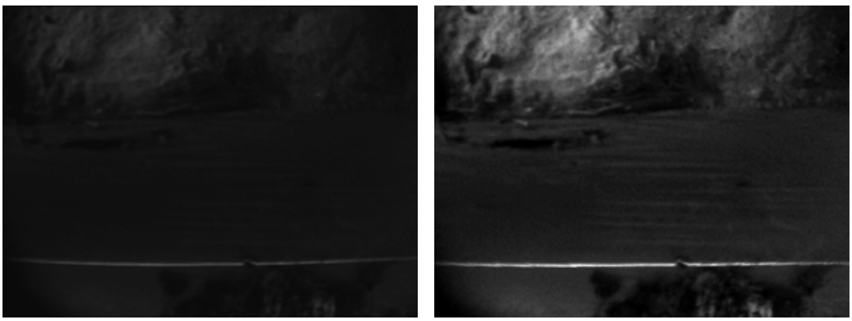

Fig. 2. (a) Original image, and (b) Red channel after lens distortion correction

3.2 Filtering

Due to reflections and stray external light entering the enclosed area of the harvester, there is significant amounts of noise in the red channel. Simple thresholding is insufficient to remove this noise in all cases, and so a filtering approach is employed. A 5x5 highpass kernel is applied to the image, and a simple threshold applied to identify regions of with significant high frequency content. As the lighting conditions are relatively stable, a constant threshold is appropriate and sufficient. As can be seen in figure 3, this operation retains the line, and removes the majority of the unwanted areas, leaving only isolated regions which should not unduly affect the Hough transform.

3.3 Hough Transform

The Hough transform is a generalised algorithm for detecting both analytic and non-analytic curves in an image using the duality between points on the curve and its parameters [4,2]. When applied to the case of straight lines, the relevant parameters are the angle of the line and its perpendicular distance from the origin. When represented this way, each point in the binary image can be represented in the Hough domain (θ, r) by the equation

$$r(\theta) = x\cos(\theta) + y\sin(\theta) \tag{1}$$

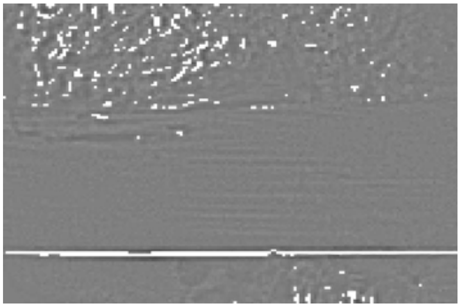

Fig. 3. Result of highpass filtering and application of threshold

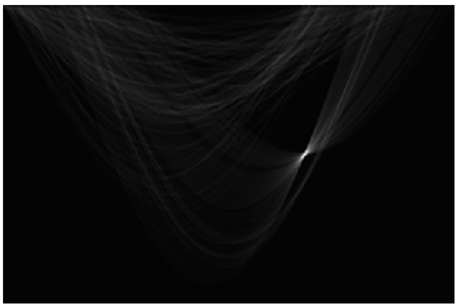

Fig. 4. Hough transform

By tranforming each point in the image into the Hough domain, a likelihood map for each possible line is obtained. For images which contain only a single line, this will appear as a strong peak in the Hough domain, and is easily isolated.

Applying the Hough transform to the result of the filter operation results shows such a result, seen in figure 4. A clear peak is evident in this image, corresponding to the laser line in the image. The position of the peak is identified, and used to calculate the position of the line in the image. This is shown in figure 5, with the detected line almost perfectly overlaying the laser line in the image.

The Hough transform is computationally expensive, as each point in the image must be transformed into a curve in the Hough domain. In order to improve the efficiency of the operation, it is possible to limit the range of the transform in (r, θ) space. In particular, the range of θ can be safely reduced, as the angle of the laser will in practice will not generally exceed the range $-\pi/6 \leq \theta \leq \pi/6$. By limiting the transform to this range, a large increase in speed can be achieved. As a precaution, in situations where the previously detected line angle nears these boundaries, it is increased.

3.4 Distance and Angle Estimation and Error Correction

Once the position of the laser line has been determined, the distance of the harverster to the bed can be calculated. This is done at two points at either end

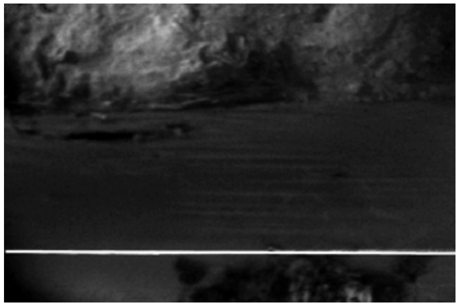

Fig. 5. Detected line

of the line, in order to also calculate the angle of the harvester relative to the bed. Firstly, the vertical position of the line y is converted to an angle θ_r relative to the camera position. This can be performed using the lens characteristics, and is easily verified by manual measurement. The actual angle of depression θ_d can then be caluated by adding this value to the angle of the camera θ_c (41°). The distance to the bed d can then be calculated by

$$d = \frac{h}{\tan\theta_d} \tag{2}$$

where h is the height of the camera relative to the laser. The average distance of the harvester to the bed is then calculated by averaging the values of d for the beginning and the end of the line. The direction of the harvester relative to the bed ϕ can also be easily calculated using simple trigonometry. These values are then used in a simple control system which manages the steering control motors of the harvester. This control system has additional rules for dealing with erroneous inputs (varying significantly from previous values) in order to provide stability in the case of vision errors.

4 Experimental Setup and Results

In order to test the algorithm presented above, two experiments were carried out. In the first, images were collected for known position and orientation of the harvester, and then analysed to determine the accuracy of the system. These images were collected in a real strawberry harvesting environment, taken at regular invervals along the row. Each image was then processed independently, and the results compared to the known data. The results of this testing are shown in table 1. As can be seen from these results, the algorithm performs very well, with over 95% of images giving near-perfect results.

Most errors are caused by large amount of noise in the input image, usually as a result of too much external light entering the enclosure. This if often caused by obstacles on the bed lifting the rubber sheeting for brief periods of time. An example of such an image, with the corresponding erroreous result is shown in

Table 1. Results of experiment 1, showing percentage of trials falling into various accuracy ranges

Angle $\phi(°)$	**Distance Error x (cm)**		
	$\mathbf{x \leq 2}$	$\mathbf{2 < x \leq 5}$	$\mathbf{x > 5}$
$\phi \leq \mathbf{5}$	95.6	1.3	0
$\mathbf{5} < \phi \leq \mathbf{10}$	0	0.4	0
$\mathbf{10} < \phi \leq \mathbf{20}$	0	0	0.2
$\phi > \mathbf{20}$	0	0	2.5

figure 6. In this case, the algorithm detected the sharp boundary between the plant material and the sheeting as the line, rather than the correct laser line at the bottom of the image. The high amounts of external light present in this image are clearly visible in the lower left.

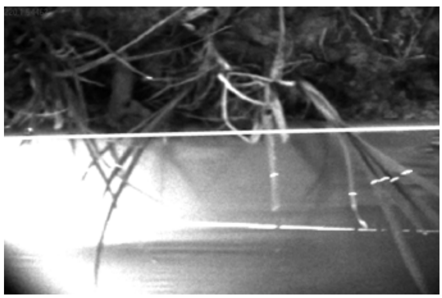

Fig. 6. Input image with large amounts of external light, resulting in error.

The second experiment tested the actual performance of the entire guidance system. In this test, the harvester was under fully autonomous control, relying completely on the output of the vision system for navigation. Testing was carried out in a number of weather and lighting conditions and in many different row configurations. Success was measured by the ability of the harvester to keep within picking distance of the bed and at a correct angle for the entire row. This was achieved in 100% of trials, with a total of 10 hours of continual operation without error.

5 Conclusions and Future Work

This paper has presented an inexpensive, image processing based approach to distance detection for the specific application of an automated strawberry harvester. By capturing images of a laser-generated line reflected from the bed, and applying a selection of filters and the Hough transform, an accurate and robust estimate of both distance and direction can be obtained. Experimental results show an extremely high accuracy, with field testing when connected to an appropriate control system showing almost perfect performance.

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