ELSEVIER Computers and Electroncis in Agriculture 16 (1997) 165–175

Computers and electronics in agriculture

Row-following accuracy of an autonomous vision-guided agricultural vehicle

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Accepted 5 August 1996

Abstract

This paper seeks to establish the accuracy of an autonomous vehicle working in a field of transplanted cauliflowers. The main sensing systems, odometry and image analysis, are briefly described as is the control system which is based on a fusion of the two data sources using a Kalman filter. Experiments to establish accuracy are described. These were carried out on four plots of cauliflowers with varying degrees of disruption to the visual scene. The RMS error of vehicle lateral position control was 20 mm, while the RMS error of estimated vehicle position was about 10 mm. Little effect of the disruption on position control was observed. It is concluded that these accuracies would be sufficient to control a vehicle and an associated crop treatment device but that improvements to the vehicle controller would make the control of the treatment device easier.

Keywords: Robotics; Control; Image analysis; Weeds; Row crop

1. Introduction

In recent decades, farming in the western world has come to rely more and more on chemical crop protection. At present approximately 23,000 tonnes of chemicals are used annually in the UK at a cost of about £400 million. Lately this heavy use of chemicals has provoked demands from consumers and environmentalists for reduction. A potential way of meeting these demands is the use of precision techniques for various types of agricultural operations, in particular the application of chemicals of all kinds so that they are placed where they will have an optimal effect with minimum quantity.

The work described here is part of our research to develop the technology for controlling an autonomous vehicle for precision crop protection. Our aim is to sense our targets on-line and to work on a plant scale, that is with an accuracy of a few

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PII S0168-1699(96)00031-2

centimetres relative to the plants themselves. This is in contrast to existing work on spatially selective operations (e.g., Stafford and Ambler, 1994) where field maps are built up from prior knowledge and treatment areas are on a scale of a metre or so based on an absolute coordinate system.

The vehicle is fitted with various sensors, the two types considered here being odometry and image analysis which are used together to derive guidance information. Image analysis is also used for differentiating between plants, weeds and soil (Brivot and Marchant, 1996) but this work is not reported here.

The present work is confined to situations where plants are established in rows and this paper reports on work to measure guidance accuracy in a cauliflower crop. We outline briefly the vehicle and its control and sensing systems. We then describe our experimental work to establish the accuracy of crop row following before reporting results and making some conclusions.

2. Vehicle control system

2.1. Vehicle hardware

The vehicle presently in use is based upon a commercially manufactured tool carrier intended for use on horticultural plots. The vehicle was originally manually driven, but has been adapted for automatic control (Fig. 1). A petrol engine drives the two front wheels via independent hydrostatic transmission units. Automatic control is permitted by using DC servomotors to set the transmission ratios of the two hydrostatic units. Rotary incremental encoders allow odometric measurement of the motion of the driven wheels with a resolution of 1792 counts per revolution. The on-board computer system consists of a portable 486 PC with an interface to a transputer network. The PC provides the user interface. All control and sensing (including image analysis) functions are carried out using the network of Inmos T800/T805 transputers.

2.2. Control system

The vehicle control software runs on a single Inmos T805-30 transputer and is fully described by Hague and Tillett (1996). A block diagram of the system is shown in Fig. 2. The speeds of the driven wheels are measured using the odometric counts, and maintained at the demanded values using feedback control. The sum of the two wheel speeds is fixed by the demanded vehicle forward speed, and the difference is used to steer the vehicle. If the speeds of the two driven wheels are denoted by (v_1, v_2), then the forward speed $s = (v_1 + v_2)/2$ and the steering rate $d = (v_2 - v_1)/W$, where W is the wheelbase of the vehicle. In order to follow a given path, in this case a set of crop rows, the path tracking controller calculates d as follows:

$$d = K_p y + K_d \theta$$

where y is the measured lateral offset from the desired path, and θ is the orientation error. In this case it may be shown (Hague and Tillett, 1996) that the system has a

Fig. 1. Autonomous vehicle in a field of cauliflowers.

second order response with natural frequency f_0 and damping factor ζ given by:

$$f_0 = \frac{1}{2\pi}\sqrt{-K_p s}, \quad \xi = \frac{-K_d}{\sqrt{-4K_p s}}$$

In practice, a constant value is used for K_p, chosen by experiment to give the desired response. In order to give critical damping at all speeds, a constant value is not used for K_d, but the value of K_d which gives $\zeta = 1$ is computed at each iteration of the controller.

2.3. Position estimation

In order to follow crop rows using the above scheme, it is necessary to determine the vehicle position with respect to the rows. Two sources of positional information are used to maintain an estimate of vehicle position. An image analysis system, which is outlined in the following section, provides a measure of the vehicle offset and heading relative to the rows. In addition to this the odometers, when used in conjunction with a model of the vehicle kinematics, give a measure of the vehicle motion. These two sources of information are combined using an extended Kalman filter (EKF) (Bar-Shalom and Fortmann, 1988).

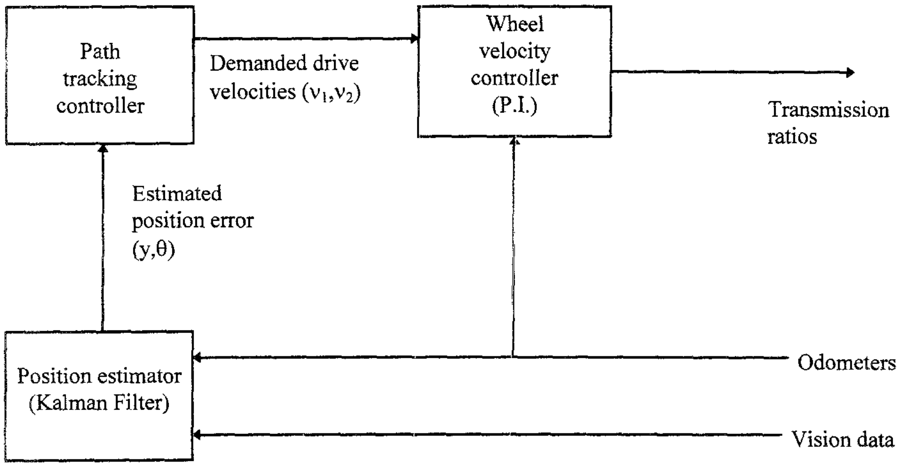

Fig. 2. Block diagram of the control system.

The (EKF) produces updated position estimates at 20 ms time steps. The filter functions in a predict/correct fashion as follows. Assume that valid data from the image analysis system was received at time step j, and denote the estimated vehicle position or state at time step j based upon vision data up to and including that at time j by

$$\hat{x}(j\,|\,j)$$

At time step, $j+1$ this old state estimate is used in conjunction with the incremental wheel motions measured by the odometers over time interval $[j,j+1]$ to predict, using a kinematic model of the vehicle, the updated state estimate

$$\hat{x}(j+1\,|\,j)$$

This prediction process is repeated at each time step until fresh vision data becomes available at (say) time k. At this point the predicted state

$$\hat{x}(k\,|\,j)$$

based upon previous vision data and.odometric measures is corrected using vision data $y(k)$ giving a corrected estimate

$$\hat{x}(k|k).$$

The correction process exploits stochastic models of the errors present in the odometric and image analysis measurements to achieve a near-optimal combination of data from the two sources. Furthermore, this stochastic information allows image analysis measurements which do not fall within a given confidence interval (in this case, 90%) of the odometry based prediction to be identified and discarded. This affords a degree of robustness to erroneous data.

An important feature of this position estimation procedure is that several predict steps may be performed between successive corrections, and thus position estimates can be generated and supplied to the control system at a higher rate than that at which the raw image analysis data is available. Moreover, the filter interpolates over vision data which is missing or rejected as erroneous.

3. Vision guidance system

The problem of finding direction from row crop plant structure has received some previous attention. Most authors have recognised that real images are likely to suffer from problems such as incomplete row lines and poor contrast between plants and background. Brandon et al. (1989) use near infra red wavelengths to enhance contrast while Reid and Searcy (1986) use a Hough transform to deal with incomplete lines. A few authors make use of knowledge in addition to the fact that the lines are reasonably straight. For example Gerrish and Stockman (1985) use an autocorrellation technique to make use of the periodicity in the image (i.e., several lines of equal spacing), they also use the known optical configuration to derive a template of converging lines which can be matched with the image. Schoenfisch and Billingsley (1993) use two or three rows and make use of the known row spacing in their regression to deal with the problem of missing parts of rows. All these authors use fields of view wide enough to include several rows and the vanishing point in the image.

Brivot and Marchant (1996) have shown that segmentation of plants, weeds, and soil is possible using infra-red images where the field of view is up to 5 by 5 plants, i.e., of the order of 2m square. A larger field of view (i.e., a lower magnification) would not allow texture details, which are effective in differentiating plants and weeds, to be resolved. With a smaller field of view there is less information for identifying the row structure which will be used for vehicle guidance. This means that any technique using a close-up view must be extremely robust to uncertainty in the data. Uncertainty is a generic problem in analysing scenes containing biological objects (Tillett, 1991). In our case uncertainties arise from variability in planting pattern, different plant sizes, presence of weeds, image noise due to natural lighting variations, missing plants, and many other causes. One approach is to use two cameras, one for guidance (with a wide field of view) and one for plant identification. This is a possibility but would result in extra system complexity. Although a wide field of view might seem to be an advantage in that there is more data, much of it is some distance away from the vehicle and could lead to significant errors especially if the rows are not straight. An alternative, used in this work, is to make as much use of the data and prior knowledge as possible, and to use a robust method to find the row structure in the image.

The Hough transform (Davies, 1990) is such a robust method. It is often used to find fairly simple structures in images such as lines or circles. Evidence for a line, for example, is amassed by calculating parameters (slope and intercept) for all lines from which the image feature could have come. This results in plotting a curve in the parameter space for each feature, for a line the 'curve' is in fact straight. If there is only one line of features in the image the curves will cross in a single point which identifies the slope and intercept. With real data there may be many crossing points so the feature space has to be smoothed and a peak found. Also there may be more than one line giving more than one peak in the feature space. The technique is tolerant to missing parts of the lines and to outliers, i.e., features that do not lie on the line, providing the number of outliers is reasonably small compared with the number of true data points.

Although normally used for simple abstractions, the technique can be modified for more complex ones providing a suitable parameter space can be derived. Marchant and

Brivot (1995) have derived a Hough transform that can find plant rows in a close-up image. They have also implemented it at a rate (10 Hz) fast enough to update the sensor fusion component of the vehicle control system. In this case the abstraction is a set of points (the plants) which are in rows of approximately constant spacing. The rows are parallel but undergo a perspective transformation from the world to the image. Noise sources include missing and misplaced plants, and weeds. Using this special Hough transform means that the evidence for the row structure is integrated over each row and also over more than one row in the image. Extra rows support each other in the Hough space and this increases the evidence available compared with a technique that finds individual rows, and so increases the robustness of the system. Marchant and Brivot used a special purpose hardware unit, controlled by a transputer, to extract the position of each blob in the image. The blob positions were used as features for the Hough transform, the loading and subsequent searching of the space being done with the transputer. Test showed that typical differences between the algorithm and a human assessment of the row structure position were 12.5 mm of offset and 1° of angle. However, this performance takes no account of errors due to the calibration between vision and world coordinates. Errors due to this source are included in the work of this paper. The reader is referred to Marchant and Brivot (1995) for a full description of the method.

4. Experimental method

Trials were carried out in two beds of transplanted cauliflowers, each approximately 70 m long extending in a north/south direction. The vehicle speed was 0.7 m/s. The beds consisted of three rows of plants with nominal spacing between the rows of 483 mm and nominal spacing along the rows of 457 mm. The plants were established in a rectangular pattern and were approximately 200 mm high. The plots were not weeded and, although weed infestation was not severe, it was appropriate for a normal commercial crop. The crop was subject to normal growing variability with the occasional missing and misplaced plants.

The area was divided into four sections to simulate various degrees of disruption to the visual image of the row structure. The first section was left as it was grown. In the second section plants were removed at three approximately equally spaced stations along the bed. These stations were 1.5–2.0 m long and thus approximately filled the field of view of the camera. At the first station four plants were removed, at the second eight, and at the third two. The disruption was randomly positioned over the station. In the third section plants were added to simulate weeds. Once again three stations were used with four, eight, and two additions. In the fourth section the last two treatments were combined, i.e., plants were removed and added (in other words displaced), in three sections of four, eight, and two displacements. As the field of view was about 15–18 plants, these disruptions represented a considerable disturbance to the visual scenes.

The camera was a normal CCD device (Panasonic WV-CD20) with the infrared blocking filter removed, and a filter fitted to cut out most of the visible band (Wratten 89B). Thus the near infrared region was used to enhance contrast between vegetation

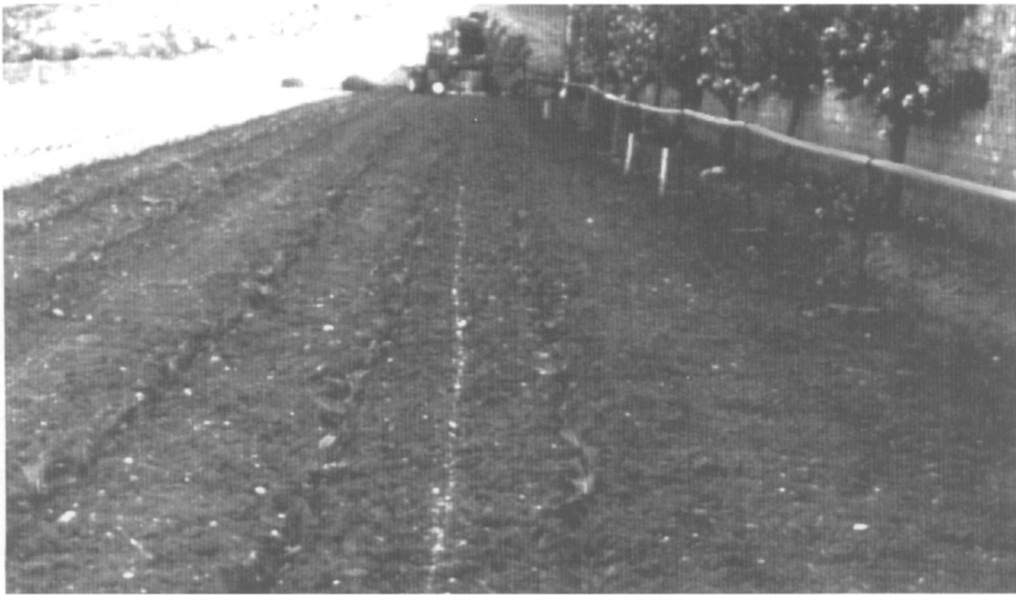

Fig. 3. Example paint trail from an experimental run.

and soil. The vehicle was fitted with a small tank which held diluted white emulsion paint. This paint was fed by gravity through a valve to a nozzle and dribbled onto the soil when the vehicle moved so recording the vehicle's position. An example paint trail is shown in Fig. 3.

It is not obvious what to measure in order to establish the accuracy of row following as the 'position' of the row structure is rather subjective. As well as the individual plant positions being vague (the centre of the plant viewed from above? the position where the plant emerges from the soil?. . .) the plant rows are not at an exactly uniform spacing and the rows are not exactly straight. The position of the row structure at each plant along the rows was established by the following pragmatic method. The plant at the western side of the bed was used as a reference. If the plant was absent its position was estimated by interpolation from the surrounding plants along the western row. The position of each plant was taken as the middle of the plant leaf area seen from above. The distances across the row structure to the middle plant and the far (eastern) side ones was measured to the nearest 5 mm, interpolating for missing plants. The row structure lateral position was taken to be the average of the three measurements, including zero for the western plant. The vehicle lateral position was measured as the distance from the western plant to the paint trace. All results are plotted as differences between the row structure position and the vehicle position. The choice of reference position (in this case the western plant) is thus inconsequential as the value cancels out in the difference. The offset between the measured row position and the measured vehicle position was removed by subtracting the mean value of the difference before presenting the data. This offset occurs due to the arbitrary positioning of the paint nozzle.

5. Results

5.1. Vehicle positioning accuracy

Fig. 4 shows the error in vehicle position for the four sections of cauliflower bed. The rectangular blocks at the bottom of each graph denote the areas of disruption. The effect of the disruption on the vehicle position is difficult to predict for a number of reasons. The camera looks ahead of the vehicle and so any disturbance to the row tracking algorithm begins to affect the vehicle before it reaches the disruption. This is then modified by the closed loop dynamics of the system before being seen. In addition the vehicle may be subject to disturbances, both due to offsets at startup and also by factors such as uneven ground. Although Fig. 4d exhibits a sudden change near to the middle disruption it would be unsound to conclude that this was caused by the disruption, especially since a similar change (at least the downward part) occurs in the section with no disruptions (Fig. 4a). Of course, a major factor masking the effect of visual disruptions on the vehicle path is that the fusion of odometry data with vision data has been designed explicitly to deal with such disruptions.

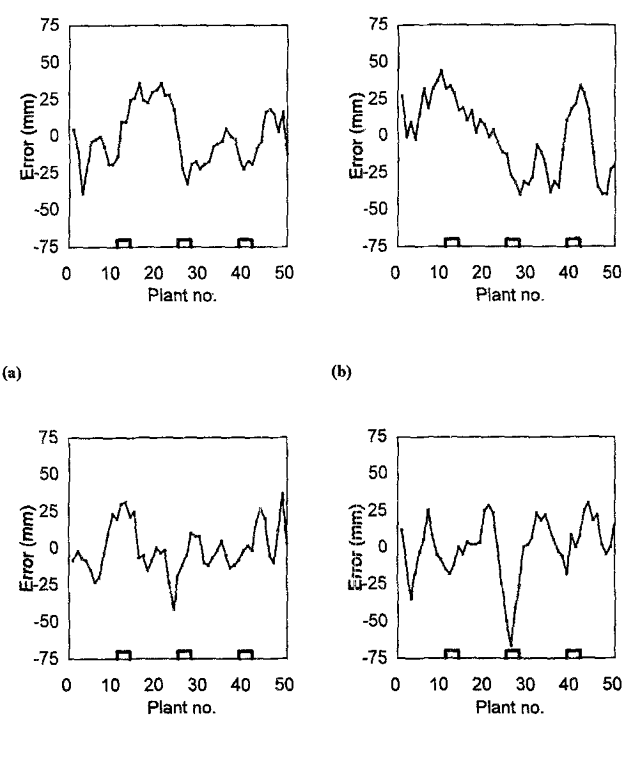

Fig. 4. Vehicle lateral position error for four sections of cauliflower bed having various levels of disruption to the planting pattern. (a) As grown. (b) Plants removed. (c) Plants added. (d) Plants displaced.

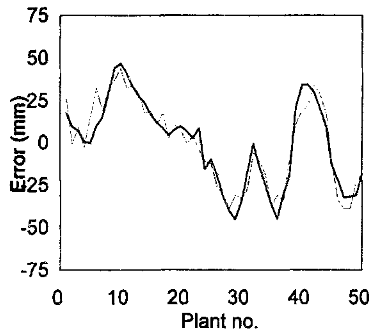

Fig. 5. Vehicle lateral position error for the run of Fig. 2(b). · · · · · ·, measured; ——, estimated with Kalman filter.

The standard deviations of the vehicle error for Fig. 4a–d are 19, 24, 16 and 20 mm. The overall standard deviation was 20 mm. Use of an F test to determine whether any of the standard deviations from Fig. 4b–d is significantly different from the undisrupted section value showed that only one showed a difference (Fig. 4b) and then only at the 5% level. There is little evidence therefore to suggest that the disruptions to the visual scenes had any effect on the control accuracy.

5.2. Accuracy of position estimate

In our final application, and within reason, control need not be very accurate providing the sensors can determine the vehicle position with respect to the plants to be treated. Inaccuracies can be accommodated by suitable fine control of the treatment device. In the case of a bank of closely spaced spray nozzles this would be achieved by switching the appropriate ones on or off. The limits of accuracy must, however, be set so that the vehicle does not damage the crop by driving too close to it and any errors in position must be within the range of the treatment device. This section examines the ability of the control system to estimate the vehicle position rather than to control it.

In addition to the manually measured offset data described above, the control system's internal estimate of vehicle offset generated by the EKF was recorded at each cycle of the controller. If the vehicle were fitted with a treatment device which can be directed using the estimated offset, then the difference between the EKF estimated and measured offset would govern the treatment accuracy. In the graph of Fig. 5, both the measured vehicle offset, and the EKF estimated offset at each measurement point are shown for the trial shown in Fig. 4b, which gave the greatest difference from the trial on the undisrupted bed. Visually the two traces agree quite closely, with much of the discrepancy within the bounds of measurement error. A statistical analysis shows that the RMS deviation, and thus the expected estimation error, was 8 mm.

6. Conclusions

We have demonstrated control of an autonomous vehicle to follow rows in a field of cauliflowers. In the form reported here the controller fuses odometry data with vision data using a model of the vehicle's kinematics and a Kalman filter. Four sections of cauliflower were used with varying degrees and types of disruption to the visual scene.

The standard deviation of the vehicle path with respect to the row structure was 20 mm for the whole set of runs. No significant effect of disruption on the vehicle path accuracy could be observed. The error was confined to a band within ±45 mm except for one short excursion to 66 mm. We conclude that this accuracy is sufficient for vehicle positioning.

When considering the accuracy with which a treatment device may be directed, the accuracy of the position estimation is of importance rather than that of vehicle control. The RMS deviation between the offset estimate generated by the EKF and that measured manually was found to be of the order of 10 mm. It should be noted that a portion of this error arises from the lack of a rigid definition of how exactly the location of the row should be measured, and also the 5 mm resolution with which the manual measurements of row position were made. Since our aim is to target treatment within a few centimetres, we conclude that the accuracy of position estimation is sufficient to allow control of a treatment device.

The trial results show that the accuracy of position estimation (8 mm for trial (b)) is somewhat better than the accuracy of vehicle control (24 mm in the same trial). Although the current level of performance is adequate to avoid damage to the crop, improved performance may simplify control of the treatment device. Improved control accuracy is an area for future work; in particular improvements in the performance of the control of wheel speeds by the use of accelerometers to provide both improved speed measurements and acceleration feedback.

Acknowledgements

This work presents results from two collaborating projects at SRI. The first is funded by the Biotechnology and Biological Sciences Research Council under the Clean Technology Programme. The second is partly funded by the Douglas Bomford trust.

References

Bar-Shalom, Y. and Fortmann, T.E. (1988) Tracking and data association. Academic Press, San Diego.

Brandon, J.R., Searcy, S.W. and Babowicz, R.J. (1989) Distributed control for vision based tractor guidance. Paper No. 7517 ASAE winter meeting, Baton Rouge.

Brivot, R. and Marchant, J.A. (1996) Segmentation of plants and weeds using infrared images. Acta Horticulturae.

Davies, E.R. (1990) Machine vision: Theory, algorithms, practicalities. Academic Press, London.

Hague, T. and Tillett, N.D. (1996) Navigation and control of an autonomous horticultural robot. Mechatronics.

Gerrish, J.B. and Stockman, G.C. (1985) Image processing for path finding in agricultural field operations. Paper No. 3037 ASAE summer meeting, East Lansing.

Marchant, J.A. and Brivot, R. (1995) Real time tracking of plant rows using a Hough transform. Real-Time Imaging., 1: 363–371.

Reid, J.F. and Searcy, S.W. (1986) Detecting crop rows using the Hough transform. Paper No. 3042 ASAE summer meeting, College Station Texas.

Schoenfisch, M. and Billingsley, J. (1993) A comparison of automated guidance systems for a variety of operations in the growing of cotton. Proc. International Advanced Robotics Programme 3rd Workshop on Robotics in Agriculture and the Food Industry, Brisbane, July 1993, pp. 8–16.

Stafford, J.V. and Ambler, B. (1994) In-field location using GPS for spatially variable field operations. Comput. Electron. Agric., 11: 23–26.

Tillett, R.D. (1991) Image analysis for agricultural processes: a review of potential opportunities. J. Agric. Engin. Res., 50: 247–258.