DEVELOPMENT OF A TRACKING AND GUIDANCE SYSTEM FOR A FIELD ROBOT

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ABSTRACT
Small robots operating between crop rows need another guidance system than existing guidance systems for larger equipment. Some experiments were done to detect crop rows and to track the motion of the vehicle. Crop row detection was based on excessive green. Motion tracking was based on dynamic template matching.
The applied methods have good perspectives although improvements are still necessary. The most important are combining information from several consecutive images and using information from the images itself to determine the required parameter values for dynamic template matching.

INTRODUCTION

Automatically guided robotic vehicles will perform many agricultural operations in the future. Until recently, automatic guidance has been limited to tractors and other larger equipment. Currently, there is an interest in developing smaller vehicles or robots that operate between crop rows. These robots are fitted with cameras that operate at a small distance above the ground, which requires the development of new vision techniques for guidance, tracking, and detection purposes.
Most of the traditional vision systems developed for guidance have been operated above the crop. Vision systems for row guidance are usually looking forward and observe several crop rows. Hough transform techniques have typically been used to identify the different crop rows. Vision systems for row tracking in mechanical weed control are usually looking downward, perpendicular to the soil surface. The plants in the row are detected to follow the crop row. Vision systems on small in-row robotic vehicles are also looking forward, but they do not have an overview over the crop; they can only see the row between the two crop rows. To guide these vehicles through a crop new navigation techniques have to be developed. This paper describes the development of a machine vision based guidance system for in-row robotic vehicles.

MATERIALS AND METHODS

The development of the system was divided into three steps. In the first step images were acquired, in the second step the rows were identified, and in the third step the images were connected to each other to track the motion.

Image acquisition

The images were acquired with a Sony DCR-VX2000 3CCD video camera in a corn crop with a height of about 25-30 cm. The camera was mounted on a small cart and pushed manually through a field. Images were taken of several rows and with camera slant angles of 15°, 25°, and 35°. The images were first stored on tape and digitized afterwards with a frequency of 2.5 images/s with a FlashBus framegrabber controlled by a C-program. Each image series consisted of 200 images, corresponding with a track length of about 100 m and a duration of about 80 s. The size of the recorded images was 640 x 480 pixels, which was reduced to 600 x 450 pixels during frame

grabbing because of limitations of the frame grabber. Further image processing was done with LabView.

Row identification

The first step in row identification was converting the image to an Excessive Green image. Excessive Green is equal to 2*G-R-B. This conversion is very suitable for the detection of green objects (plants) in an image and is rather insensitive for differences in lighting conditions and the presence of shadows (Woebbecke *et al.*, 1995). This image was then converted to a binary image by setting a threshold on the Excessive Green value.

Weed plants between the rows would interfere with the row edge detection and were removed by removing all non-border connected objects from the binary image. The images were taken such that the plant rows were border connected in most images in the sequence.

The second step was identifying the virtual end point of the row. This point was found by making a histogram of the number of object pixels in horizontal (image row) and vertical (image column) direction. The image row with the maximum number of object pixels is the Y coordinate of the virtual end point. The X coordinate was determined by searching for the minimum number of object points in the column histogram. Searching was done from both left and right side and the X coordinate was equal to the average of the positions of the first minimum from both left and right side.

The third step was detection of the crop row edges by a search and linear regression procedure. Each image row was searched starting at the centre (the X coordinate of the virtual end point) for the first object point at both the left and right side. After searching all image rows, linear regression was used to calculate the crop edge lines at the left and the right side.

Image tracking

Image tracking was realised by dynamic template matching. The template was created by taking a subimage of size 120 x 80 pixels centred at (300,240). The best corresponding position for this template was determined in the consecutive image by the pattern matching algorithm of LabView. This algorithm uses image understanding techniques to interpret the template and uses this information to find the template in the image.

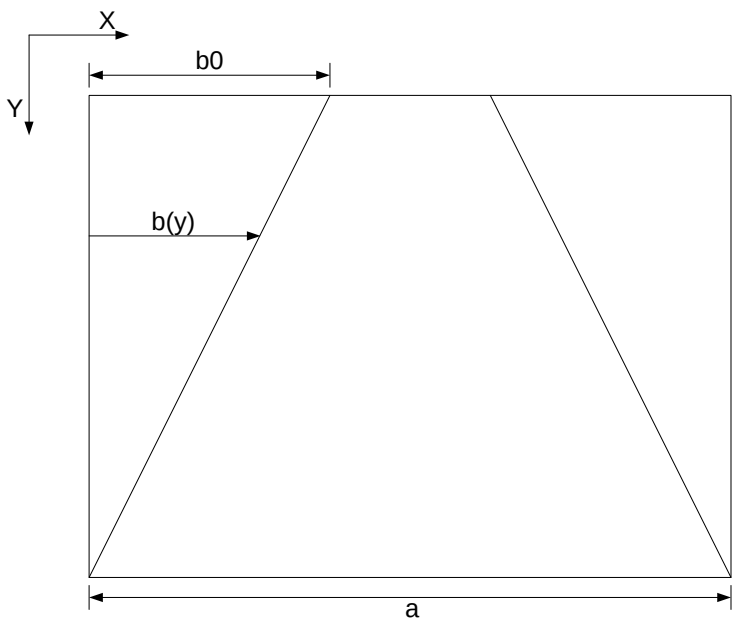

Figure 1- Parameters for calculation of the distortion factor.

The slant view of the camera with respect to the ground level resulted in that rectangular objects became trapezoids and that objects became bigger when they were closer to the camera. Three different scaling factors (1.0, 1.15, and 1.3) in combination with three distortion correction factors (1.0, 0.95, and 0.90), and only scaling correction were tested to find the best match. The distortion factor df is equal to 2*b0/a (Figure 1). For a non-distorted image the factor is equal to 0 (b0=0); for a triangular image (vanishing point at y=0) it is equal to 1.0 (b0=a/2), and for images with a vanishing point in the image it is > 1. The distortion factor is based on y=0 but is calculated for each image row independently (df(y)=2*b(y)/a). An overview of the different scenarios and the corresponding numbers is given in Table 1. Scenario 0 is the starting scenario without any correction for scaling and distortion.

Table 1 - Overview of the different scenarios and corresponding values for the scaling and distortion factors for image and template (df).

		df					df	
Scenario	Scaling	image	template		Scenario	Scaling	image	template
0	1.0				4	1.0		
10	1.15	-	-		5	1.15	0.95	0.262
11	1.3				6	1.3		
1	1.0				7	1.0		
2	1.15	1.0	0.286		8	1.15	0.90	0.242
3	1.3				9	1.3		

The distortion was removed by stretching both the triangular (df=1.0) or trapezoidal (df<1.0) image and the template image to a rectangular image. The distortion removal of the template required different values for the distortion factor (0.286, 0.262, and 0.242 respectively); calculated for the Y-value corresponding with the top of the template.

Only the images taken with the slant angle of 25° were used to test the different scenarios. For this angle, images of two different rows (1 and 2) and two directions (forth (A) and back (B)) were available. Image tracking was assessed based on the number of found matches between images, the quality of the matches (a number between 0 and 1000, where 1000 corresponds with a perfect match), and the distance between the centre of the template and the found match in the consecutive image. The lower bound for the match quality was set to 300. Matches with a lower score were neglected and considered as not found.

RESULTS

Crop row identification

The results of the crow row identification are shown in Figure 2. In general the procedure found a proper line to identify the edge at both left and right side. In some situations the procedure failed; mainly caused by weeds in the centre of the row and connected to the corn plants.

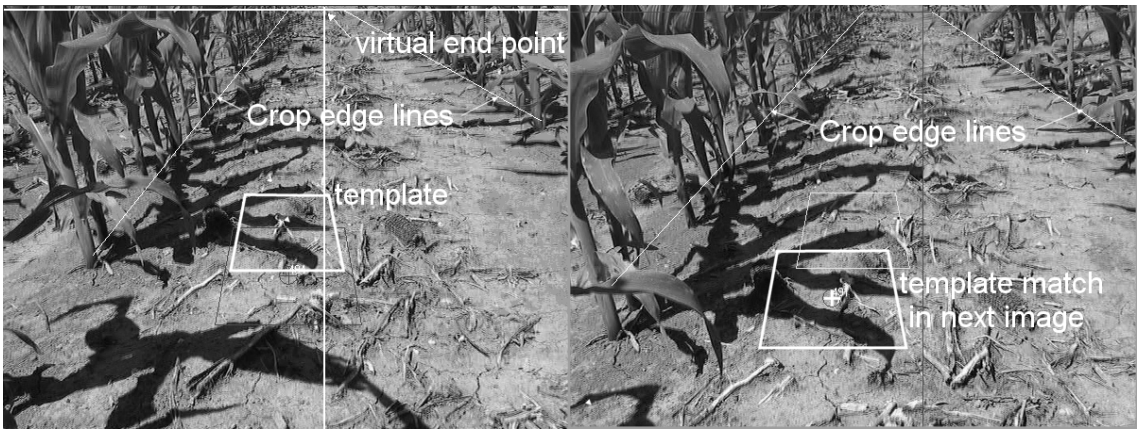

Figure 2 - Crop edge lines as identified by the program. The figure also shows the virtual end point, the template, and the corresponding match of the template in the consecutive image.

Number of matches

An overview of the number of matches >300 for the different image series and the different scenarios is given in Figure 3.
The figure shows that there is a large difference between the number of matches for the series 1 and the series 2. Image series 1 has a larger number of matches, which is due to that the area between the crops rows was cleaner (less large weeds) than the area for image series 2. In both image series the back direction shows a larger number of matches than the forward direction; this is however coincidence. Very clear is that in all cases scenario 11 (only a scaling correction) gives the highest number of matches.

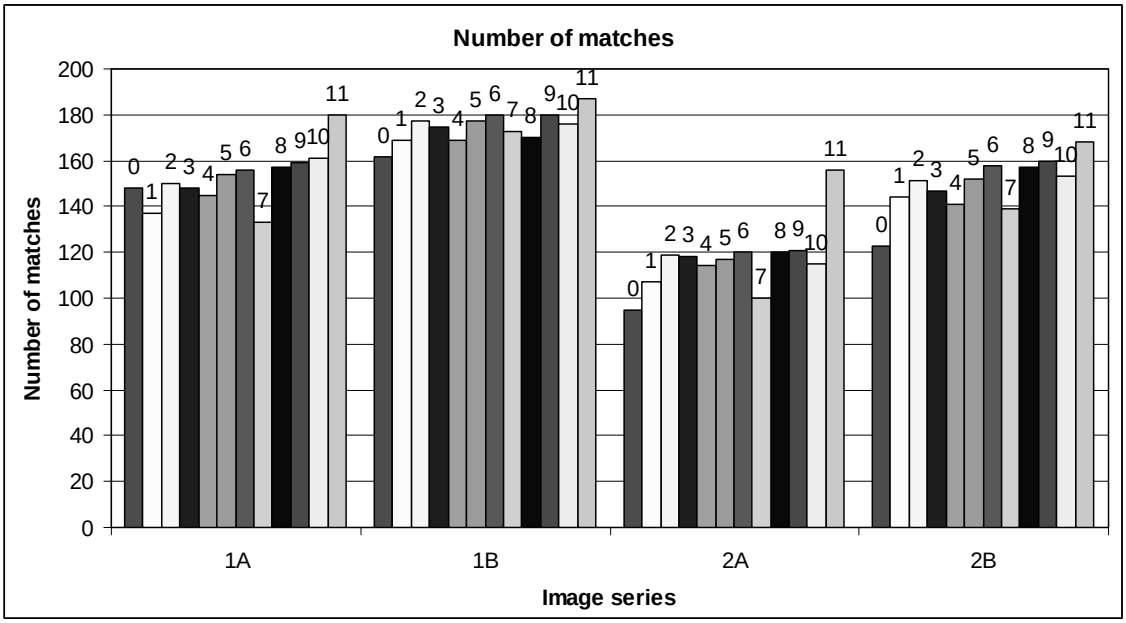

Figure 3 - Overview of the number of found matches for the different image series and scenarios. The numbers above the bars are the scenarios.

Quality of the matches

An overview of the quality of the matches for the different images series and the different scenarios is given in Figure 4. The figure shows that the quality of the matches is better for image series 1 than for image series 2. In both cases the series B are slightly better than the series A. This is however coincidence. As with the number of the matches, the quality of the matches is also the highest for scenario 11.

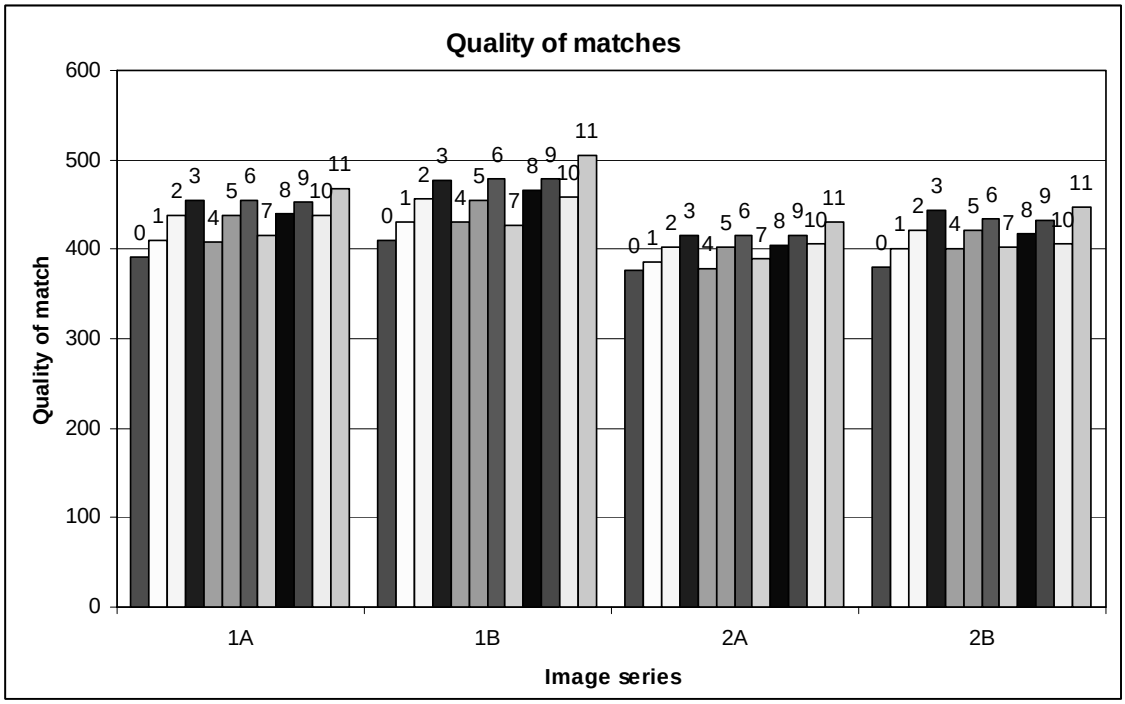

Figure 4 - Overview of the quality of the matches for the different image series and scenarios. The values are the averages for the found matches. The numbers above the bars are the scenarios.

Distance between template and found match

An overview of the positions of the found matches for images series 1B and the scenarios 0 and 11 is shown in Figure 5 and Figure 6 respectively. Comparing both figures shows that besides the number of matches, the deviations between the

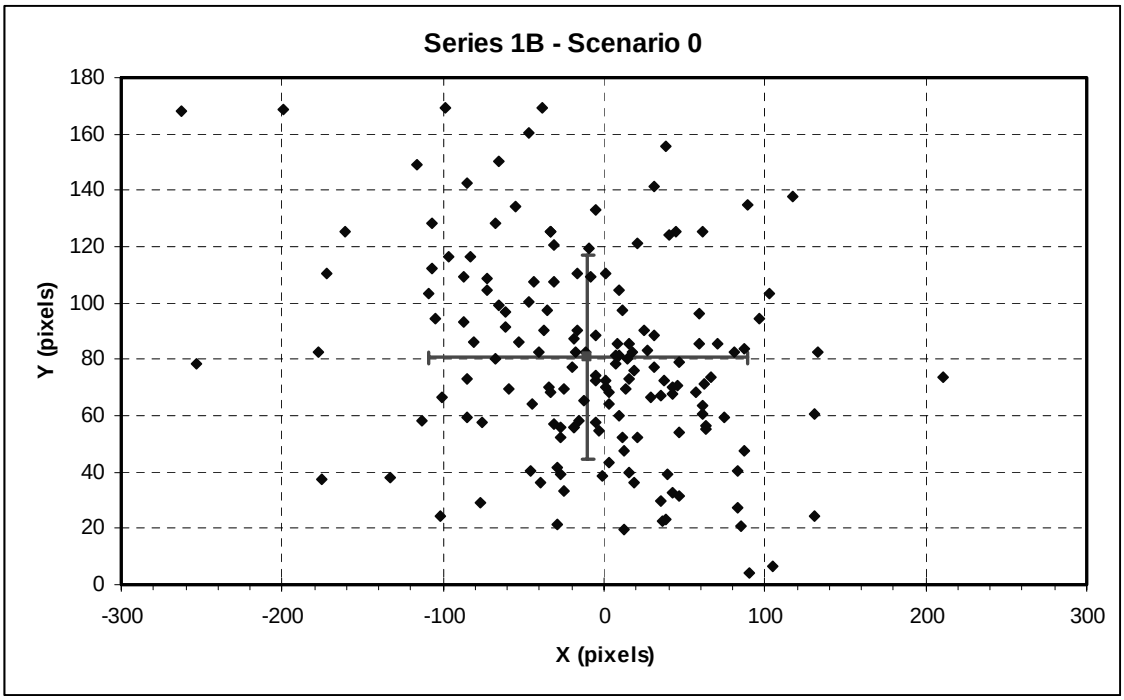

Figure 5 - Distance between template origin and the found match in the consecutive image for image series 1B and scenario 0. The cross identifies the average and the length of the bars corresponds with 1.0 standard deviation.

template origin and the match point in the consecutive image are much closer to each other in Figure 6 than in Figure 5; the spread is also less. In the most ideal case the X value should be equal to 0 and the Y value equal to a distance corresponding with the travelled distance between the images.

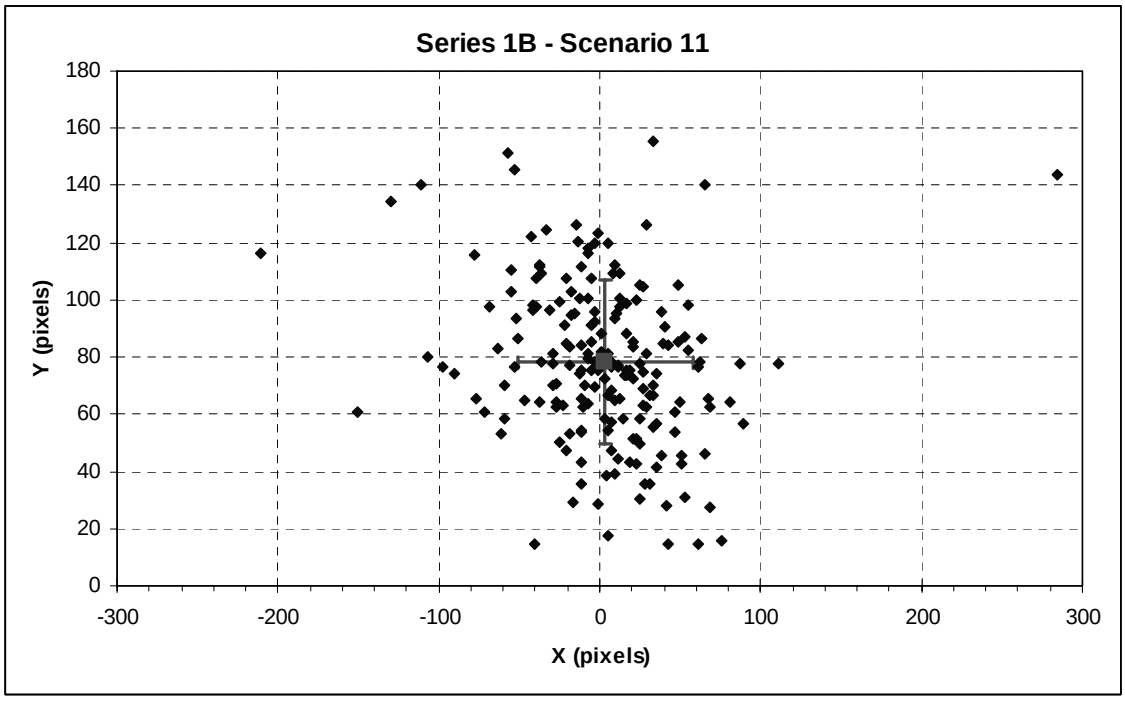

Figure 6 - Distance between template origin and the found match in the consecutive image for image series 1B and scenario 11. The cross identifies the average and the length of the bars corresponds with 1.0 standard deviation.

The averages and standard deviations for all image series and scenarios are given in Table 2. The data in this table are in line with what is shown before regarding the number of matches and the quality of the matches. A high number of matches and a good quality of the matches correspond with a relative small standard deviation.

Table 2 - Overview of averages and standard deviations for the distances between template origin and found match in next images for the different image series and scenarios. The numbers in the boxes correspond with the data in Figure 5 and Figure 6.

	Series 1A		Series 1B		Series 2A		Series 2B	
	Average	St.dev.	Average	St.dev.	Average	St.dev.	Average	St.dev.
0 X	29.0	123.9	-9.9	98.7	0.1	181.4	-34.9	155.9
Y	71.3	34.9	80.6	36.2	76.0	41.7	88.2	40.7
10 X	23.5	86.2	-13.1	93.0	-23.9	154.7	-30.3	126.5
Y	68.7	26.2	79.8	32.1	74.2	35.9	79.6	35.7
11 X	7.1	42.5	3.2	54.5	-0.2	64.3	-14.5	95.7
Y	65.2	18.8	78.3	28.7	68.8	28.1	79.8	34.5
1 X	86.1	169.1	-61.1	167.2	72.0	253.0	-86.5	195.0
Y	71.0	35.9	75.5	36.9	77.7	40.2	82.4	41.5
2 X	52.6	130.9	-39.6	134.5	72.3	214.2	-53.1	149.6
Y	67.2	28.9	77.4	33.4	72.0	37.1	74.4	34.6
3 X	38.9	104.7	-40.6	125.0	58.0	167.0	-42.9	149.9
Y	67.6	24.7	75.5	28.7	73.8	32.8	74.5	32.0

	Series 1A		Series 1B		Series 2A		Series 2B	
	Average	St.dev.	Average	St.dev.	Average	St.dev.	Average	St.dev.
4 X	73.3	162.7	-42.7	170.9	45.9	256.6	-72.1	196.8
Y	69.9	34.2	81.2	36.6	77.0	39.3	81.2	42.8
5 X	53.3	119.1	-37.4	143.7	43.5	200.4	-44.2	128.1
Y	66.9	26.8	78.6	33.9	72.4	35.6	76.4	36.1
6 X	30.3	84.2	-27.5	116.4	45.9	171.0	-53.6	134.7
Y	66.8	22.2	76.9	29.5	71.6	32.7	77.0	34.0
7 X	75.5	153.3	-41.0	159.7	71.7	239.4	-58.3	187.9
Y	70.3	33.5	79.3	37.8	75.7	42.4	78.6	43.2
8 X	38.6	112.1	-40.0	130.9	47.5	202.3	-49.4	139.3
Y	67.3	26.6	77.0	33.0	76.3	37.0	77.9	36.1
9 X	41.4	108.1	-23.3	105.5	13.4	174.5	-42.1	133.0
Y	67.0	24.0	75.5	28.5	70.8	31.6	76.5	32.9

DISCUSSION

The crop row identification is until now only judged on the basis of visual observation. For a better quantification of the quality of the line the found lines should be compared with the real lines. However, these lines can only be found by manual interpretation of the images, which is also subjective.

An improvement of the crop row identification will be when the identification will not be only based on the image itself but also on previous images. The position of the line cannot change that much when a certain number of lines in the previous images were at almost the same position. The lines should also be defined in a coordinate system with the virtual end point as origin.

The matching of the images shows that only scaling is the best improvement to find the match in two consecutive images. Distortion correction slightly improves the matches but the most important factor is scaling. This result was rather surprising. The matching algorithm of LabView may cause it. It is not a straight correlation algorithm but an algorithm that uses techniques as geometric modelling of the image, non-uniform sampling, and extraction of template information that is rotation and scaling independent. These techniques may profit from the scaling correction but not from the distortion removal.

The data of the distance between template centre and match show that the standard deviation in both X and Y-direction is smaller when the quality of the matches is higher. Remarkable is that most average distances for the X-direction for the two A series are positive and negative for the two B-series. This needs further investigations. The deviations in X-direction are rather good for scenario 11; the deviation from the centre line is relatively high for the other scenarios.

Real matching errors are not determined yet. This requires manual determination of matching points in consecutive images and comparison of them with matching points found by the program.

CONCLUSIONS

Excessive green is a good parameter to discriminate the crop row from the background. The crop row edge search and regression procedure results in general in a good crop edge line although some improvements are possible and necessary. Comparison of different scenarios showed that the scenario with only scaling correction gave the best results. It has to be mentioned that the matching may be interfered by the specific implementation of the matching algorithm by LabView. The matching procedure has to be further improved to realise 100% number of matches between consecutive images.

REFERENCES

Woebbecke, D. M., G. E. Meyer, K. Von Bargen, D.A. Mortensen (1995) Color indices for weed identification under various soil, residue, and lighting conditions. Transactions of the ASAE 38(1): 259-270.