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A region and contour based technique for automatic detection of tomato roots in minirhizotron images

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Summary

The use of minirhizotrons is a common tool to investigate fine roots turn-over in a variety of ecosystems. Manual analysis of the resulting images is very time consuming, however. An improved approach for automatic root detection combining region and contour based techniques was developed. The first step is aimed at detecting easily recognizable parts of the root (optimally at least one part of each root), which will be called a R-SEED subsequently in this paper. In a second phase each R-SEED is expanded with a more sophisticated algorithm to find the boundaries of the complete root. 14 time series with 3 to 8 images of tomato fine roots were digitized, processed and used to validate the approach. As the R-SEED detection influences the overall performance strongly the approach benefits from the improved algorithm. In four out of five images from one time series examined in detail the root area detected is nearly correct with an relative error between -8.8% and +7.3%. In one image the detection fails substantially due to decomposed roots. In general, the root area detected is systematically lower than the area marked manually.

Introduction

The minirhizotron technique is a suitable tool to observe growth and longlivity of fine roots, changes of root dynamics and size, as well as the activity of root systems (SMIT et al., 2000). It is therefore widely used in root studies of various ecosystems (UPCHURCH and RITCHIE, 1983; MAJDI and PERSSON, 1995; MAJDI, 1996; HENDRICK and PREGITZER, 1996; SMIT et al., 1994). In contrast to destructive methods (e.g. soil coring) this technique allows for long term *in situ* observation of individual roots. Qualitative measurements of variables such as root color and root branching can be made along with quantitative measurements of root growth. Although root numbers can be counted directly in the field images are usually recorded in analog form on video-tapes or as digital images. For statistical analysis a large number of replicates is necessary for the quantification of root dynamics. In our field experiment 56 minirhizotrons were used to investigate the influence of saline irrigation water on the root dynamics of tomato roots (BRECKLE et al., 2003). Nine root inventories covering a complete growing season resulted in more then 26,000 images. The evaluation of such a large number of images is very labor and time intensive. Therefore, an automatic image analysis system is an ideal tool for root growth evaluation. Several approaches for manual, semi-automatic and automatic analysis of minirhizotron images were developed in the recent decade (SMUCKER et al., 1987; RICHNER et al., 2000). An interactive image program was used by HENDRICK and PREGITZER (1996) to measure the changes of root length. An automated image analysis algorithm was successfully used for washed root samples (DOWDY et al., 1998), but the detection of roots in minirhizotron images is more complex due to the soil background. For some types of soil the captured roots appear brighter (or darker) than the soil background and gray level thresholding can be used for the differentiation of roots in such cases (CASARIN et al., 1991; ANDRÉN et al., 1996). However, this kind of technique is very inaccurate for the more common case of inhomogeneous background and illumination.

In this paper we present an improved approach for automatic image analysis based on the identification of root contours. It extends our original approach, which was completely contour based (JANKOWSKI et al., 1995), by taking more global information into account. A new region based technique to detect a part of each root as a starting point for further processing is introduced. These parts are called R-SEEDS in this paper since they are expanded to incorporate the complete root contour in a subsequent step as described in JANKOWSKI et al. (1995). The new approach was tested on video images of tomato roots and is described in detail.

Material and methods

Minirhizotron installation and video images acquisition

Experiments were conducted in lysimeters situated at the 'Arava Research Station' in the southern Arava Valley (Israel). Free standing lysimeters with 200-l capacity were filled with local sandy loam soil. A detailed description of the lysimeter system is given in BEN-GAL and SHANI (2002). In each lysimeter one tomato plant was planted and daily irrigated (BRECKLE et al., 2003). Four glass minirhizotrons (length 70 cm, outer diameter 300 mm) were installed vertically in the lysimeters 12 cm away from the lysimeter edge. For the root observation a technical endoscope was used (Storz 81482 Tuttlingen, Germany). The endoscope had a 90° field of view and observations were made in four directions every 5 cm. The observed image area is 0.8 cm^2. A cold light source was used for lighting. To minimize illumination problems the endoscope was placed on one side in the tube. A colour CCD camera (Kappa CF 11/2, Göttingen, Germany) was mounted on the endoscope and video images were recorded on VHS-tapes with a commercial video recorder (Sony).

Digitization and preprocessing of images

To validate automatic root detection, time series of various video tapes were digitized using a digital VCR (Panasonic NV-HS950) and a Cyperoptics frame grabber card (PXC-200L). The resulting digital images are sized 768x576 pixels (PAL) with a resolution of approximately 1800 dpi. There are black rows and columns at the border of the images due to a grabbing artefact (Fig. 1a). These are discarded before further processing by removing 15 pixels from each side resulting in the central 738x546 pixels of the original image. An 11x11 median low pass filter proved to be ideal to cope with the large amount of noise in the images; edges containing important gradient information for the expansion step are retained while substantially reducing noise.

Image analysis

In order to automatically detect roots in minirhizotron images our approach is composed of two phases: R-SEED detection and

expansion (JANKOWSKI et al., 1995). Fig. 1 shows an example for a minirhizotron image and results of both phases.
As described before a R-SEED is defined to be a short part of a root. It is used as a starting point for consecutive expansion to complete the root in the phase of R-SEED expansion using an A*-based algorithm. The original gradient based R-SEED detection developed by JANKOWSKI et al. (1995) employs local information only; it yields unsatisfactory results for low contrast images as considered in this work. The original algorithm is modified in this paper to use a globally oriented region based approach for seed detection. Motivation for this approach is the observation, that in virtually all cases at least a small part of each root is projected as a homogeneous area into the minirhizotron image. Therefore, the image is binarized using a set of varying thresholds (Fig. 2a for one example). Connected component analysis is used to detect regions in each of the resulting binary images. Regions are selected as R-SEEDS if they fulfill a specific shape criterion. This criterion constrains admissible length, width, width to length ratio, and area of the region as well as the curvature of the borders (see ERZ and POSCH, 2003 for further details of this definition). The resulting regions are very likely to be part of a root. Obviously, all regions fulfilling the above shape criterion can be detected testing all possible thresholds (255 for 8 bit gray level images). However it proved stable to test possible thresholds with a coarse discretization first and refine the search subsequentially. A substantial speed up is achieved using this strategy.

Next, the border of each R-SEED is enhanced for more accurate localization. To this end suitable pixels at both ends of a R-SEED are selected, their position adjusted to the locally maximal gradient magnitude and combined into pairs (see Fig. 2b). The two pixels pairs of each R-SEED are then optimally connected taking shape and gradient information into account (see Fig. 2c). An A*-algorithm is used for this border enhancement similar to the one used in the following expansion step.
The A*-algorithm is an efficient heuristic search algorithm to find an optimal path connecting two nodes in a search graph. For our application each node of the search graph consists of two image pixels of the left and right boundary of a root opposite of each other. The cost function employed is specific to the application and a heuristic estimate of remaining costs are used to speed up the search. The cost function is defined such that the path detected describes parallel contours located on locally maximal gradient magnitudes and thus conforms to the root model. The result of this search is a contour which normally fits the intuitive perception and provides an optimal starting point for subsequent seed expansion (Fig. 2c). The expansion step has been described in detail in JANKOWSKI et al. (1995) and will not be repeated here.

Results and discussion

To evaluate the approach – detection of R-SEED as described in the last section and expansion as in JANKOWSKI et al. (1995) – we used 14 time series of tomato root images with 3-8 images per time series (Fig. 3). Results will be discussed for one time series consisting of 5 images. For quantitative evaluation, all images were labelled manually marking each pixel as a root or backgrund (i.e. soil) pixel (Fig. 4). In the following, we take this manual classification as ground truth. Thus, we neglect errors resulting from manual processing and underestimate the correctness of the automatic results as a consequence.
One relevant and often used criterion for the quality of root detection is the number N_d of roots that were detected compared with the number N_p of roots present. However, the root area A_p projected onto the image reflects changes in root growth much better. Therefore we additionally consider the root area A_d detected. The resulting relative error E_A, as well as the sensitivity Se and specifity Sp when classifying pixels as root or soil is analyzed to assess the accuracy. In all evaluated images soil pixels outnumber root pixels by far. As a

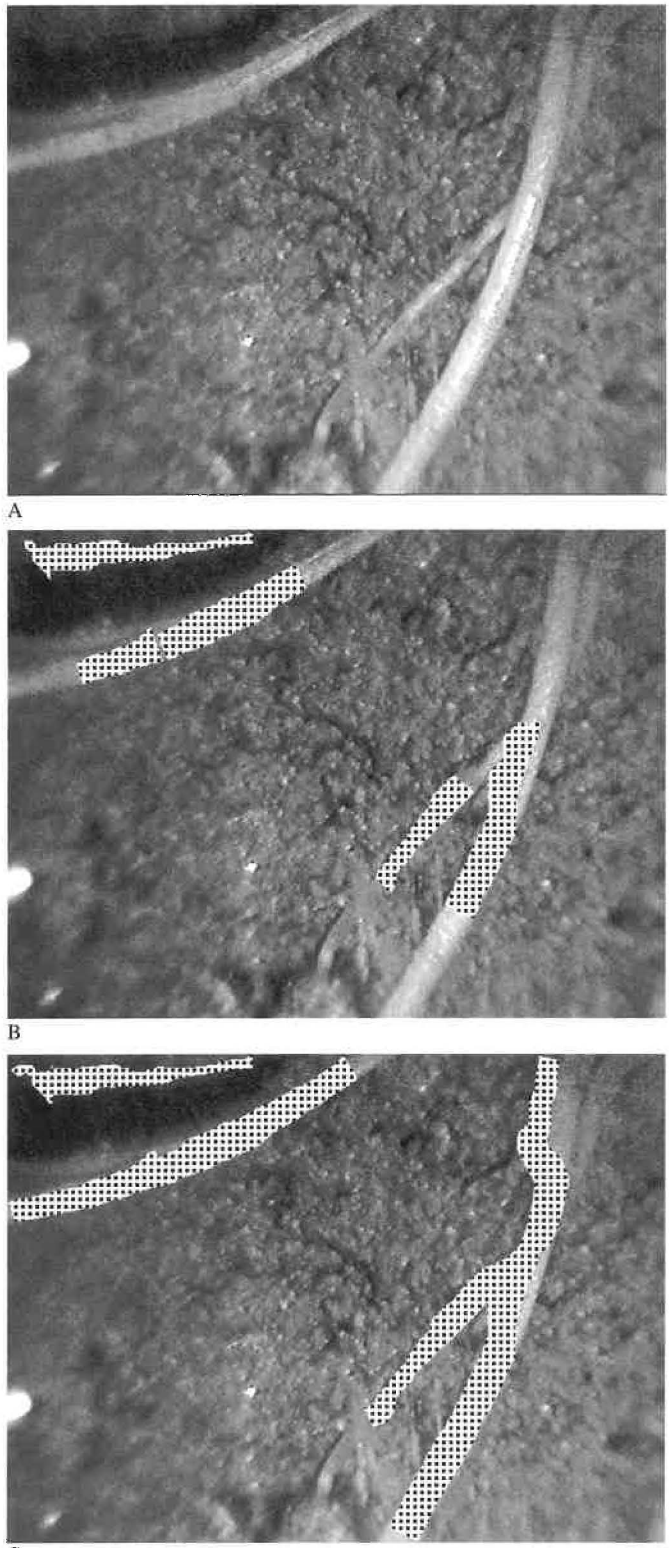

Fig. 1: Illustration of the two phases of the root detection: (A) original image, (B) Detection of R-SEEDS, (C) detected roots resulting from expanding R-SEEDS.

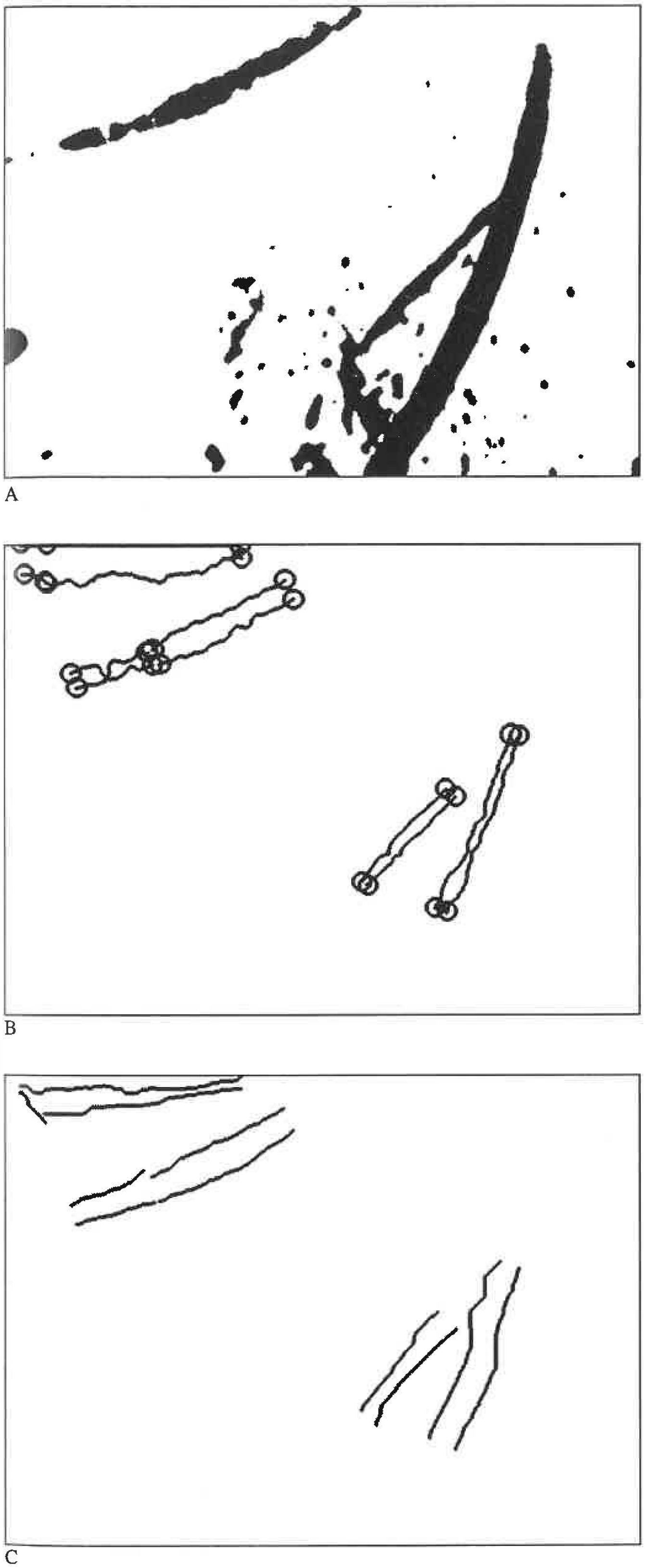

Fig. 2: Processing steps of R-SEED detection: (A) binary image resulting from one specific threshold, which is optimal for the upper left region, (B) all regions selected as R-SEEDS using a set of varying thresholds: borders from thresholding and pixel pairs to be connected by the A*-algorithm, (C) final R-SEEDS resulting from A*-connection. These are the R-SEEDS shown in Fig. 1 using a different representation

consequence the relative error of incorrectly classified pixels E_p is usually very low but uninformative and we focus on sensitivity and specifity of root pixels.

The definition is as follows:

$$Se_{root} = \frac{P_{cp}}{(P_{cp} + P_{fn})}$$

$$Sp_{root} = \frac{P_{cp}}{(P_{cp} + P_{fp})}$$

$$E_A = \frac{A_d}{A_p} - 1 = \frac{P_{cp} + P_{fp}}{P_{cp} + P_{fn}}$$

Here P_{cp} is the number of pixels correctly classified as root pixel (drawn black in Fig. 4), P_{fp} is the number of pixels incorrectly classified as root pixel (false positive, displayed light gray) and P_{fn} the number of pixels incorrectly classified as soil pixel, i.e. pixels which are root pixels but are classified as soil (false negative, dark gray).
Root sensitivity and specifity are defined according to the intuitive meaning: sensitivity measures how much of the root area was found by the algorithm, i.e. how sensitive the algorithm reacts. The latter one describes how many of all pixels labeled as 'root' are root pixels indeed. It therefore is a measure of how specific the results are. Both measures should ideally be 100%. Results achieved on the presented time series range from 34.2% to 86.0% for the sensitivity and from 49.5% to 72.9% for the specifity (Tab. 1). Results for images Fig. 3a to Fig. 3d are very well in the range to be expected. However, the algorithm fails to a great extent to detect the root area in image Fig. 3e. This is partially caused by strong blurring of a large part of the root at the top of the image. The fact that the root area marked manually on the right hand side belongs to a dead root has an even stronger impact; it can hardly be distinguished from the background without using information from earlier images, knowledge which is currently not exploited by the algorithm.

Tab. 1: Results for each of the 5 images of the time series displayed in Fig. 3. Sensitivity Se_{root} and specifity Sp_{root} of root pixels, sensitivity Se_{soil} and specifity Sp_{soil} of soil pixels; relative error E_A of root area detected; relative error E_p of total pixels classified incorrectly.

Image	Se_{root}	Sp_{root}	Se_{soil}	Sp_{soil}	E_A	E_p
1	53.9%	59.1%	97.6%	97.1%	-8.8%	5.0%
2	67.6%	67.1%	96.0%	96.1%	0.7%	7.6%
3	78.2%	72.9%	96.9%	97.7%	7.3%	5.2%
4	59.2%	62.5%	97.3%	96.9%	-5.3%	5.7%
5	34.2%	49.5%	98.1%	96.6%	30.9%	-5.4%

Image no. 1 reveals a typical problem of the contour based expansion. Refraction in conjunction with low gradient magnitudes in the upper right part of the image cause the detected contours to be located aside the projected root. This is caused by the presence of parallel structures with high gradient magnitudes
However, the correct expansion can be determined employing colour information which are not yet taken into account. Despite these

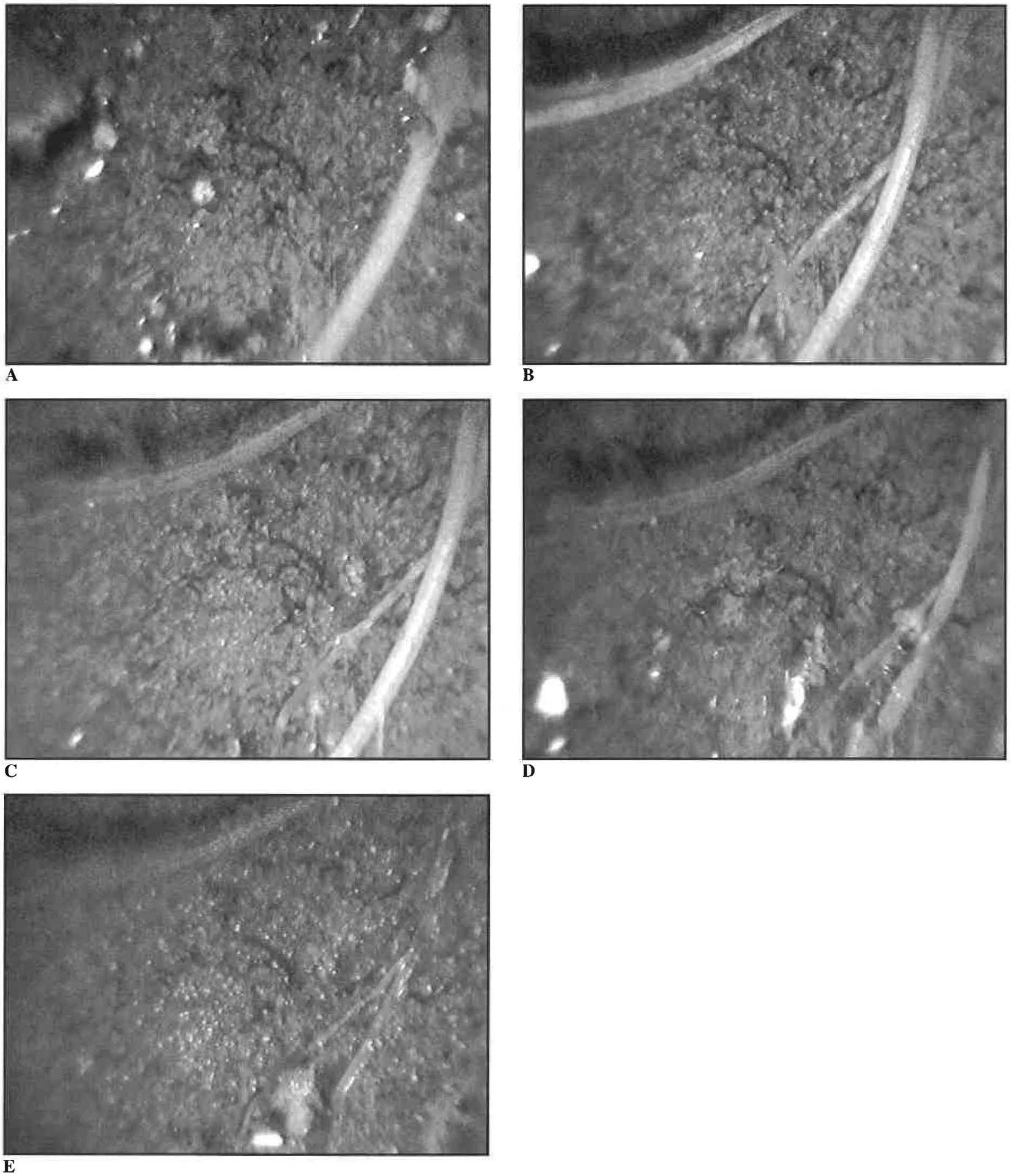

Fig. 3: Original minirhizotron images of tomato roots (1-5) recorded in 10 days intervals used for the validation of the approach described.

inaccuracies in most cases all roots could be detected, with the detected root area usually being too small. This systematic behavior is illustrated in Fig 5. Observation of root area changes, such as shrinking root diameters of dying roots, is of great biological importance. Therefore, root area reflects changes of root functions better than the root number.

Problems still arise if roots do not fulfill the shape criterion employed currently by the algorithm, e.g. branchings of a root. Extending the current root model to allow for such more complicated root shapes (branchings) and by taking additional features into account can thus further improve results. In addition, higher contrast and homogeneous illumination would aid the detection process allowing the expansion of R-SEEDS to be more accurate due to better gradient information resulting from high contrast.

Conclusions

An improved approach to detect roots in minirhizotron images presented in this paper was successfully used and validated with independed images. The new detection of R-SEED considerably improves the contour based approach by JANKOWSKI et al. (1995).

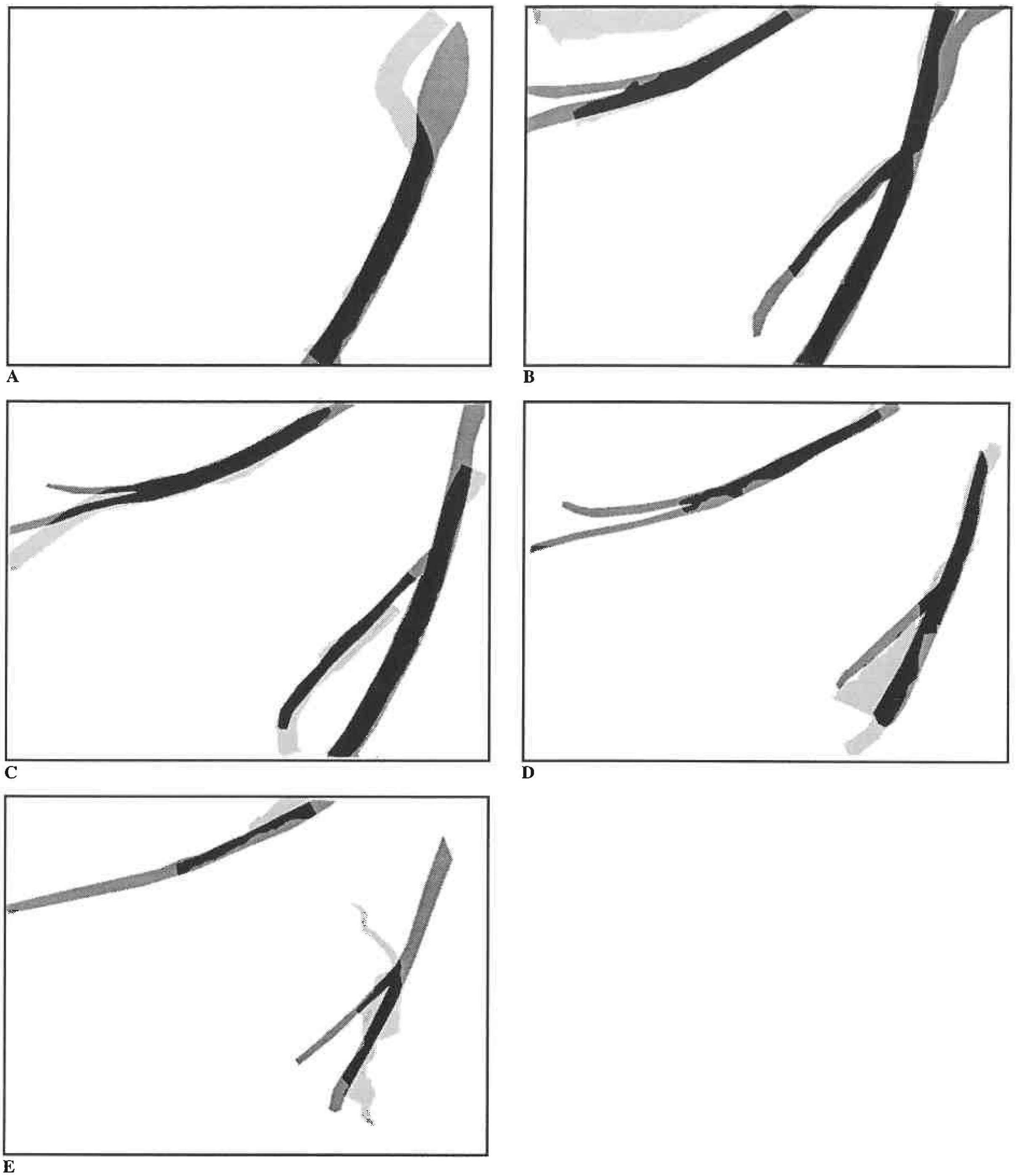

Fig. 4: Results of the image analysis of the minirhizotron images (Fig. 3) with the A*-based algorithm. Black: correctly detected root pixels, Dark grey: missed root pixels, Grey: pixels incorrectly detected as root

The root area was calculated almost correctly in four out of five images and under estimated in the fifth image by 31%. Both techniques allow already a better detection of roots with complex backgrounds than other approaches (e.g. SMUCKER et al., 1987) or colour based approaches. Future development will include a more elaborated root model and enhanced image acquisition. Another aim will be to connect expanded R-SEEDS when situated on a single root and to control termination of expansion more precisely. Additional information in the form of colour and information derived from the time dimension may prove valuable.

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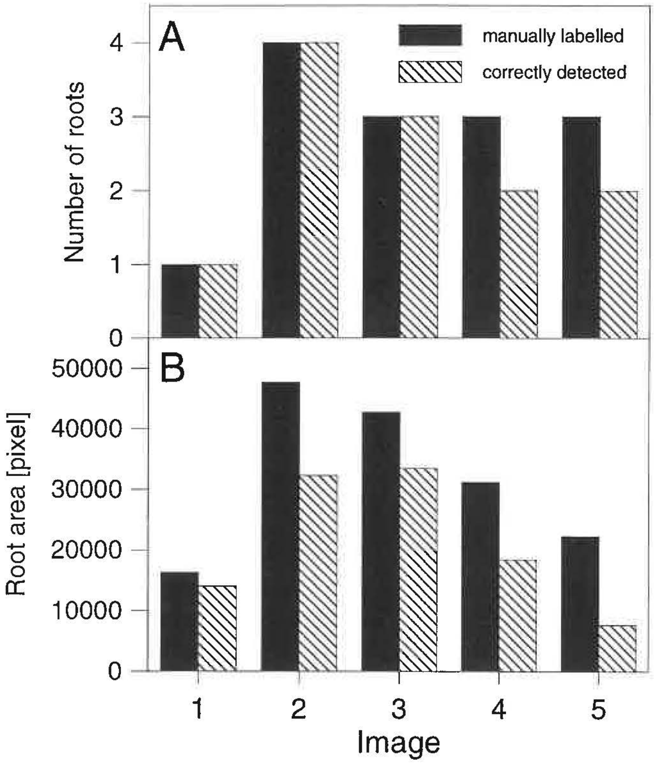

Fig. 5: Number of roots (see Fig. 4) detected by the image analysis program and manually marked (A) and detected and manually labelled root area (B).

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