ESTIMATING THE PLANT STEM EMERGING POINTS (PSEPS) OF SUGAR BEETS AT EARLY GROWTH STAGES

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ABSTRACT

Successful intra-row mechanical weed control of sugar beet (*beta vulgaris*) in early growth stages requires precise knowledge about location of crop plants. A computer vision system for locating Plant Stem Emerging Point (PSEP) of sugar beet in early growth stages was developed and tested. The system is based on detection of individual leaves; each leaf location is described by center of mass and petiole location. After leaf detection the true PSEP locations were annotated manually and a multivariate normal distribution model of the PSEP relative to the located leaf was generated. From testing the system, PSEP estimates based on a single leaf have an average error of ~ 3mm. When several leaves are detected the average error decreases to less than 2mm.

Keywords: leaf extraction, plant position

INTRODUCTION

Mechanical inter-row weeding between crop rows has been used for a long time. However, mechanical intra-row weeding within rows between the single crop plants is relatively new. Physical intra-row methods can, in general, rely on three different strategies (Griepentrog & Dedousis, 2010: chap. 11): (1) soil coverage of weeds or (2) weed root/stem cutting or (3) uprooting of weeds (whole plant or partly). The first option is only relevant in some crop types such as cereals and potatoes. Sugar beet (beta vulgaris) at the dicotyledon stage does not belong to these groups (Kouwenhoven, 1997; Melander, 2000) and only strategy (2) and (3) may be used. Several intra-row mechanical weed management methods need to know where the crop plants are located, especially with concern to the plant stem emerging point (PSEP) which is defined as the point where the plant stem emerges from the soil surface. This paper describes and evaluates a vision based method which detects single crop leaves and predicts where the corresponding PSEP is located.



Figure 1: Typical leaf shapes of sugar beets.

MATERIALS AND METHODS

The current work consists of three parts: (1) development of a leaf detector, (2) building of a relative PSEP model, and (3) using the relative PSEP model to predict true PSEP based on detected leaves.

Image acquisition

Binary images of sugar beet seedlings in growth stages BBCH10-14 (Meier, 2001) were acquired with the Robovator (Poulsen, 2010). A single pixel measured approximately 1.1 mm by 1.1 mm.

Leaf extraction

Examples of leaf shapes are shown in Fig.1. The structure consisted of a large mainly convex region attached to the rest of the plant via a thin stem (petiole) (Meier, 2001). The leaf extraction method works in two steps. First convex regions are located and marked as leaf tip candidates. From the located leaf tip candidate a search for the corresponding petiole is then initiated. If a petiole was located a leaf was found. When a leaf was detected the leaf location and orientation was described by petiole location \vec{S} and the leaf center of mass \vec{C} .

Leaf tip candidate location

Leaf tip candidates were found at local curvature minima of the plant boundary. The direction of the boundary before the point of interest is the direction of the vector connecting the current point with a point seen 12 steps earlier along the boundary. The direction of the boundary after the point of interest is calculated similarly. Boundary curvature is estimated as the difference between the orientation before and after the point of interest. Plant boundary and curvature along the boundary is visualized in Fig. 2. Local maxima correspond to concave regions. Local minima correspond to convex regions such as leaf tips. To locate a candidate leaf tip for each leaf, the following steps were used: (1) division of the

boundary into concave and convex regions, (2) location of the minima in each convex region and (3) thresholding of the located minima. The purpose of the first step was to split the boundary into segments that at most contained a single leaf tip. Locations where the curvature estimate changed sign were used as splitting points. The second step found the most likely leaf tip location, which were the points along the boundary where the boundary was convex and the change of direction was maximized. Step three removed possible leaf tip locations according to the magnitude in change of direction, if the change of direction was too small (i.e. less than 1 radians) the candidate was eliminated.

Location of corresponding petiole

From each of the candidate leaf tips a search for the corresponding petiole was initiated. Two boundary walkers were placed at the leaf tip with the goal of following the boundary in each direction, one clockwise and one counterclockwise. The movement of the walkers was controlled such that they reached the petiole nearly simultaneously. The distance between the walkers was measured during their motion. In Fig. 3 the search strategy is visualized. For each value of the distance threshold the corresponding circle was drawn together with the two walker locations. To locate the petiole, the distance between the walkers was investigated as follows: (1) search for a narrow leaf region which initiated the region in which the petiole could be located followed by (2) a search for a broadening of the leaf width which ends the region in which the petiole could be found. The leaf boundary cut-off positions were given by the location of the walkers when they were closest together during the "leaf-state". The petiole location was set to the midpoint of the two boundary cut-off positions.



Figure 2: Contour of plant seedling and the estimated curvature along the contour.



Figure 3: Visualization of the stem search procedure.

Manual marking of root/leaf relative locations

After the automatic extraction of plant leaves, real PSEP locations were marked manually. To describe the marked PSEP location relative to the extracted leaf, the leaf coordinate system is placed with origin located at the petiole \vec{S} and direction of the x axis parallel to the vector $\vec{C} - \vec{S}$. An example is shown in Fig. 6. PSEP locations were marked with a single pixel, so the average quantization error will be about 0.5 mm along each dimension. The true PSEP locations marked by an operator will also have an uncertainty. To estimate size of the typical error in this process the same image was annotated by two persons. Differences in PSEP locations was determined.

PSEP location model

A multivariate normal distribution was used to model the PSEP location relative to the leaf coordinate system. The model was defined as:

$$p(\vec{x}) = \frac{1}{2\pi |\Sigma_{lc}|} \exp\left(\frac{-1}{2}(\vec{x} - \vec{x}_{lc})^T \sum_{lc} (\vec{x} - \vec{x}_{lc})\right)$$

where \vec{x}_{lc} is the centre of the true PSEP estimate and \sum_{lc} is the covariance matrix. Both \vec{x}_{lc} and \sum_{lc} are expressed in the leaf coordinate system. Ellipses were used to visualise the multivariate normal distribution, contours of certain values are drawn such that a given fraction of the probability is inside the ellipse. The used fractions for visualization are 68%, 95% and 99.7%.



Figure 4: Leaf coordinate system and the generated PSEP location model.

Combination of relative PSEP location models

In many cases it is possible to detect more than a single leaf, an example is shown in Fig. 5. In the figure 99.7% ellipses of the two estimates of the true PSEP share a common region and it could be expected that the true PSEP was located within this region. To combine two PSEP models $(p_A(\vec{x}) \text{ and } p_B(\vec{x}))$ the probability densities are multiplied and normalised.

 $p_A(\vec{x}) \propto p_A(\vec{x}) * p_A(\vec{x})$

The parameters of the combined models were calculated directly from the parameters of models A and B according to (Gales & Airey, 2006).



Figure 5: Combination of two PSEP models.

Generation of position predictions

To test the developed method for PSEP estimation, the method was applied to a few test images. True plant locations were determined manually and compared to estimated PSEP locations. From each of the detected leaves a PSEP estimate was generated. When multiple PSEP estimates were close to each other, they were combined to provide hopefully improved estimates.

Performance evaluation

The accuracy of the estimated PSEP locations was quantified by measuring the distance from the estimated PSEP location to the nearest true PSEP location. The true PSEP locations were based on manual annotations.

RESULTS

Leaf detector performance

For evaluating performance of the leaf detector, the 805 leaves present in test images were counted manually. The leaf detector located 46.6% (395) leaves, of those were 2.4% (19) FPs.

Relative PSEP model

The leaf detector was applied to three images. True PSEPs were marked by hand in all three images. Leaves were detected by the leaf detector method and their location specific information recorded. Analyzing leaves and PSEPs led to the generation of 223 data points. In the local leaf coordinate system the multivariate normal distribution model was described by the parameter values:

$$\vec{x}_{lc} = \begin{pmatrix} 5.40mm \\ 0.24mm \end{pmatrix}$$
 and $\sum_{lc} = \begin{pmatrix} 12.65 & 1.28 \\ 1.28 & 2.35 \end{pmatrix} mm^2$

Error distribution in PSEP estimates

The errors of PSEP estimates based on one, two, three and four leaves were calculated. The distribution of errors is visualized in figure 6. 10% of the estimates based on a single leaf had an error larger than 4 mm. The similar number for estimates based on two or more leaves was below 3 mm. A huge increase in the accuracy is seen when the number of leaves is increased from one to two, additional leaves also reduce the error but not as much. When using more than two leaves the accuracy of the system was similar to the error in human annotation.



Figure 6: Errors in PSEP estimates based on one, two, three or four detected leaves compared to human annotation.

DISCUSSION

The leaf detector was not able to locate all leaves in the test images. This was due to overlapping leaves, leaves with irregular shapes and, to a certain extent, limitations in the implemented algorithm.

When the leaf detector found two leaves of a single plant the corresponding true PSEP will, with a probability of 95%, be within a distance of 5 mm or less from the estimate. Sun et al. (2010) were able to measure the position of transplanted crops with an RTK-GPS unit within 51 mm for 95% of the plants. The accuracy of the vision system was therefore one order of magnitude better than RTK-GPS mapping of plants. When three or more leaves were used to predict PSEPs the accuracy was comparable to the human annotation. One interpretation of this is that the developed method can predict PSEPs with a higher accuracy than the reference predictions based on manual annotation given that two or more leaves are detected for each PSEP.

CONCLUSION

A system for automated PSEP estimation of sugar beet plants (in growth stages BBCH10-14) based on leaf detection has been developed and tested. In a set of test images the system detected 46.7% of the present leaves. A multivariate Gaussian PSEP model was generated based on the detected leaves and manual annotation of true PSEPs. Given center of mass and attach point of a single leaf

the model stated that the average true PSEP was at a distance of 6.2 mm from the petiole attachment point and placed on the line connecting the leaf attach point and the leaf center of mass. In the set of test images the detected leaves were used to predict the true PSEPs. When several leaves of the same plant are detected, the PSEP models can be combined using least-squares estimation and thus produce an even better estimate of the true root location. For example, by combining two leaves the average error was reduced to 1.9 mm. Precise quantification of the error in three and four leaf based PSEP estimates is hindered as these methods performed on par with the human annotation used as reference.

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