Computers and Electronics in Agriculture 110 (2015) 78–90

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Modeling leaf growth of rosette plants using infrared stereo image sequences

Eren Erdal Aksoy [a,*], Alexey Abramov [a], Florentin Wörgötter [a], Hanno Scharr [b], Andreas Fischbach [b], Babette Dellen [c]

[a] Georg-August-Universität Göttingen, BCCN, Department for Computational Neuroscience, Inst. Physics-3, Friedrich-Hund Platz 1, D-37077 Göttingen, Germany
[b] IBG-2: Plant Sciences, Forschungszentrum Jülich, 52425 Jülich, Germany
[c] Institut de Robòtica i Informàtica Industrial (CSIC-UPC), Llorens i Artigas 4-6, 08028 Barcelona, Spain

ARTICLE INFO

Article history:
Received 8 November 2013
Received in revised form 21 October 2014
Accepted 23 October 2014

Keywords:
Leaf segmentation
Leaf tracking
Leaf modeling
Plant growth
Phenotyping

ABSTRACT

In this paper, we present a novel multi-level procedure for finding and tracking leaves of a rosette plant, in our case up to 3 weeks old tobacco plants, during early growth from infrared-image sequences. This allows measuring important plant parameters, e.g. leaf growth rates, in an automatic and non-invasive manner. The procedure consists of three main stages: preprocessing, leaf segmentation, and leaf tracking. Leaf-shape models are applied to improve leaf segmentation, and further used for measuring leaf sizes and handling occlusions. Leaves typically grow radially away from the stem, a property that is exploited in our method, reducing the dimensionality of the tracking task. We successfully tested the method on infrared image sequences showing the growth of tobacco-plant seedlings up to an age of about 30 days, which allows measuring relevant plant growth parameters such as leaf growth rate. By robustly fitting a suitably modified autocatalytic growth model to all growth curves from plants under the same treatment, average plant growth models could be derived. Future applications of the method include plant-growth monitoring for optimizing plant production in green houses or plant phenotyping for plant research.

1. Introduction

With increasing requirements for food due to a growing world population, optimizing plant production is becoming an important factor for the agricultural industry. Plant performance and productivity results from a complex interaction between its genotype and environment, resulting in its expressed properties, i.e. its phenotype. Thus, if one seeks to understand these interdependencies, e.g. to achieve larger yields, plant phenotypes in terms of expressed plant structure and function need to be analyzed quantitatively. For this task automatic, non-invasive methods are highly desirable, but problems arise from the complex and varying appearance of plants, making it difficult to detect and recognize relevant plant organs and growth patterns.

Previously both color and stereo vision have been used to obtain some relevant plant features, mainly for recognition and classification purposes (Loch et al., 2005; Moeslund et al., 2005; Quan et al., 2006; Biskup et al., 2007; Song et al., 2007; Jin and Tang, 2009; Alenyà et al., 2011a; Teng et al., 2011; Silva et al., 2013; Wang et al., 2013), but those procedures are error prone, or require the concourse of a user to correctly segment and characterize individual leaves. For instance, Quan et al. (2006) modeled plants directly from a set of images for a better supervised leaf segmentation. Jin and Tang (2009) detected corn plants by only using depth images without dealing with the tracking issue. Leaf tracking has, to our knowledge, so far only been performed with unambiguously identified leaves. For example, Biskup et al. (2007) tracked the leaf orientation angles, and Polder et al. (2007) used penalized likelihood warping and robust point matching of leaf contours in order to detect emerging damages caused by disease. Alenyà et al. (2011b) showed how a robot arm can track a manually selected single leaf using some geometrical characteristics and color information. The problem of tracking multiple leaves was not addressed by these works. The work in (De Vylder et al., 2013) uses active contours to track multiple leaves, but they process time lapse plant images in batch once the complete sequence is acquired. Their proposed segmentation approach is triggered with the last frame of the sequence in a semi-supervised manner and the detection phase can omit new leaves since it goes to the first frame starting from the last one. Vylder et al. (2011) combined active contours with a Bayesian framework to eliminate parameter tuning steps in the

* Corresponding author.
E-mail address: eaksoy@gwdg.de (E.E. Aksoy).

http://dx.doi.org/10.1016/j.compag.2014.10.020
0168-1699/

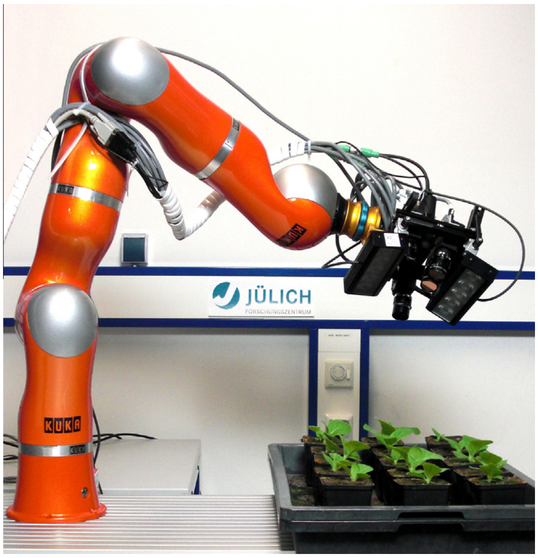

Fig. 1. Robot gardener used in the European project GARNICS. A black-and-white 5 MP camera with infrared filter and required illumination devices were mounted on a lightweight KUKA LBR4 robot arm. For each tobacco plant the robot arm captured a stereo image pair from a top view at every hour.

segmentation and tracking phases. However, they need manually segmented images to have a good estimate of the probability distribution functions for the calculation of internal and external probabilities. Both approaches (De Vylder et al., 2013; Vylder et al., 2011) have also not been tested on plant sequences that last longer than 3 days.

Along this line, the European project GARNICS (Gardening with a Cognitive System)[1] aimed at 3D sensing of plant growth and building perceptual representations for learning the links to actions of a robot gardener (see Fig. 1). The project encompassed both the long-term learning of treatments to achieve specific goals (maximum leaf growth, homogeneous plant growth) as well as the short-term robot interaction with plants (for leaf surface measurement, disocclusion, probing), and this study has been conducted in this context.

More precisely, we address the problem of sensing and controlling plant growth parameters by ways of leaf tracking and model fitting, using a stereo infrared camera set-up, monitoring tobacco seedlings during their first three weeks of growth. A major difficulty hereby arises from the complex appearance of plants in the image. Leaves are weakly textured, often overlapping, thus occluding each other, and their form may be distorted in the 2D projection due to steep leaf angles with respect to the camera view. Under these conditions, the automated image segmentation of individual leaves is highly challenging, and cannot be guaranteed. In this work, we first over-segment the infrared images and then employ a merging procedure using a 2D leaf-shape model, but also incorporating 3D information from stereo matching. The main growth curves of the plant leaves are extracted and used to analyze plant development over time. Segmentation failures appear as noise in the system, and can be handled at least to some degree. Once the main growth curves corresponding to the individual leaves of the plant are found, erroneous segments can be removed, and by using a leaf-shape model, the growth rates for each identified leaf can be computed.

Rosette plants are commonly used in plant research facilities, and the automatic growth analysis of seedlings would come in handy for many laboratories. Furthermore, growth monitoring of seedlings can be used in plant production to optimize plant treatments, e.g. with respect to the provision of water and nutrients or light requirements. Size and color distribution of plant leaves over time are important cues to monitor the lack of such requirements, avoiding plant stress situations.

Note that this study has also been described as a part of a patent (Wörgötter et al., 2013).

[1] http://www.garnics.eu.

2. Plant material

Six tobacco plants (*Nicotiana tobacum cv. Samsun*) were grown under constant light conditions (500 μE m^{-2} s^{-1}) with a 16 h/8 h day/night rhythm. Three of them (Plant IDs 79329, 79335, and 79338) received 1.8 ml of water every other hour ("Treatment 1"), the others (Plant IDs 79330, 79336, and 79339) received 0.9 ml of water and 0.5 ml of nutrient solution with 1% Hakaphos green every other hour ("Treatment 2"). Water and nutrient solution were applied by the GARNICS robot system, positioning small tubes, one for water and one for nutrient solution, at predefined locations and pumping using an automated flexible-tube pump.

In the GARNICS project, treatments were selected to produce training data for a cognitive system. The actual amounts of water and nutrient solution are therefore well adapted to the soil substrate such that the sets of plants show distinguishable performance of generally well growing plants. Finding an optimal treatment was left for the system. The soil used for the experiment ("Kakteenerde") has low nutrient content and dries relatively fast with an approximately exponential behavior $A = A_0 \exp(-t/\tau)$, where $\tau \approx .7$ days.

We applied the proposed leaf tracking and modeling algorithm to tobacco-plant sequences showing the growth from germination well into the leaf development stage, i.e. we started our observations at growth stage 09 and typically stopped at stage 1006 (according to the extended BBCH-scale presented in CORESTA CORESTA (2009)), due to size restrictions.

3. Method

3.1. Overview

Our framework for continuous measurement of plant growth parameters consists of three main parts: data acquisition and preprocessing, segmentation of all frames from a plant video sequence, and consistent leaf tracking and modeling of the segmented leaves. A schematic showing all steps of the procedure and labeled by numbers is presented in Fig. 2.

As input data we use gray-scale stereo images acquired with an infrared camera attached on a robot arm. We compared different illumination options and found that plant structures and boundaries between tobacco leaves could be detected more easily for infrared light than for visible light. In addition, plants do not react to the applied 880 nm IR light, e.g. by photosynthetic activity. Consequently, illumination and acquiring images at night is possible without influencing plant growth, in contrast to visible light. A pair of images (left and right) is captured at each time step by moving the robot head with the infrared camera and light source, providing a stereo baseline (see Fig. 2(A) and (B)). In step 1 of the procedure, we compute a depth (disparity) map from the stereo pair using a block-matching algorithm from the OpenCV library Bradski (2000) (see Fig. 2(C)). This method gave preferable results compared to other methods. We further removed the background from the scene to simplify the following computations (see Fig. 2(D)).

Next, in step 2, each preprocessed infrared image of the sequence is segmented independently. Afterwards, each leaf is represented by one or more segments as shown in Fig. 2(E). In step 3,